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Unit-Based Optimization Approaches for the Thermal Design of Residential Buildings

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A B S T R A C T

Building regulations, energy scarcity, and climate change have compelled designers to seek energy-efficient design alternatives for buildings. Current regulations only focus on the total energy requirements of buildings, disregarding the significant variations in energy performance across different units within a building, leading to discomfort among occupants. Conventional optimization approaches based on these regulations thus lack the capacity to address this issue. Addressing the variability in thermal performance within units necessitates the adoption of unit-based optimization approaches. This study elucidates the inadequacy of conventional optimization approaches and proposes two alternative methods that account for this issue. Within this framework, the thermal design of a typical five-story residential building with six apartment units on each floor was optimized using the conventional optimization approach. A simulation-based optimization system employing Distributed Evolutionary Algorithms in Python (DEAP) and Energy Plus was utilized. Differences in energy performance among different units were observed under three distinct climate conditions. Subsequently, two approaches were proposed: (i) single-phase multi-objective optimization and (ii) multi-phase single-objective optimization, with the objectives of optimizing overall building performance and balancing variance within units. The study's findings demonstrated that multi-phase single-objective optimization returned better results.

Konut Binalarının Termal Tasarımı için Birim Tabanlı Optimizasyon Yaklaşımları

M A K A L E   B İ L G İ S İ

Anahtar Kelimeler:
Birim bazlı optimizasyon
Termal performans
Genetik algoritma
Enerji verimliliği
İklim değişikliği

Ö Z E T

Bina yönetmelikleri, enerji kıtlığı ve iklim değişikliği, tasarımcıları binalar için enerji verimli tasarım alternatifleri aramaya zorlamıştır. Mevcut yönetmelikler yalnızca binaların toplam enerji gereksinimlerine odaklanmakta, bir bina içindeki farklı birimler arasındaki enerji performansındaki önemli farklılıkları göz ardı etmekte ve bu da bina sakinleri arasında rahatsızlıklara yol açmaktadır. Bu yönetmelikleri baz alan geleneksel optimizasyon yaklaşımları bu nedenle bu sorunu çözme kapasitesinden yoksundur. Birimler içindeki termal performanstaki değişkenliğin ele alınması, birim bazlı optimizasyon yaklaşımlarının benimsenmesini gerektirir. Bu çalışma, geleneksel optimizasyon yaklaşımlarının yetersizliğini ortaya koymakta ve bu konuyu açıklayan iki alternatif yöntem önermektedir. Bu çerçevede, her katında altı daire bulunan beş katlı tipik bir konut binasının termal tasarımı, geleneksel optimizasyon yaklaşımı kullanılarak optimize edilmiştir. Distributed Evolutionary Algorithms in Python (DEAP) ve Energy Plus kullanan simülasyon tabanlı bir optimizasyon sisteminden faydalanılmıştır. Üç farklı iklim koşulunda farklı üniteler arasındaki enerji performansı farklılıkları gözlemlenmiştir. Sonrasında, genel bina performansını optimize etme ve birimler içindeki varyansı dengeleme amacına yönelik iki yaklaşım önerilmiştir: (i) tek aşamalı çok amaçlı optimizasyon ve (ii) çok aşamalı tek amaçlı optimizasyon. Çalışmanın bulguları, çok aşamalı tek amaçlı optimizasyonun daha iyi sonuçlar verdiğini göstermiştir.

INTRODUCTION

The use of fossil fuels in energy generation has increased significantly due to rapid industrialization in recent decades. Environmental damage necessitates the need to decrease nonrenewable energy consumption on a global scale (Zune et al., 2020). Achieving carbon neutrality by 2050 requires promoting energy efficiency and selecting decarbonization options with no environmental side effects (Buonomano et al., 2022). In addition to mitigating climate change and local pollution, energy conservation can enhance the health of occupants and national energy supply security (Bertoldi, 2022).

The rapidly increasing energy demand on the global scale has raised a worldwide concern. Energy-efficient technologies and eco-friendly policies have been insufficient to counterbalance the demand (Kaya and Caglayan, 2023). In this direction, the European Union has aimed at achieving an energy efficiency of 32.5% by 2030. Member States need to take radical energy efficiency measures to accomplish the national energy efficiency objectives (Malinauskaite et al., 2019). The objective of Türkiye has been stated as reducing the energy intensity by 35.3% in the 2020-2035 period, which requires a major transformation in all industries (MENR, 2022).

The building industry is significantly energy-dependent and consumes approximately 40% of the total energy consumed worldwide (Somu and Ramamritham, 2020). The industry is responsible for about one-third of carbon emissions (Gao et al., 2023) and has great potential to mitigate environmental damage (Caglayan et al., 2020a). Consequently, identifying energy-efficient designs and systems for buildings has become a popular field for both researchers and designers (Yigit, 2021). In particular, determining the most efficient thermal design has been the main subject of numerous international studies (Caglayan et al., 2022).

Recently published review studies have presented new methodologies for designing energy-efficient buildings (Pooyanfar and Topal, 2018; Longo et al., 2019; He et al., 2022). A relatively new technique known as simulation-based optimization has been recognized as a promising way to analyze energy-efficient building design alternatives. The results of certain benchmarking studies show that such optimization methods can reduce building energy consumption by up to 30% (Yu et al., 2021). The general strategy for building energy optimization is presented in Figure 1. The design alternatives are provided by the optimization algorithms, and the building configuration is modified based on feedback from the energy simulation tool (Si et al., 2016).

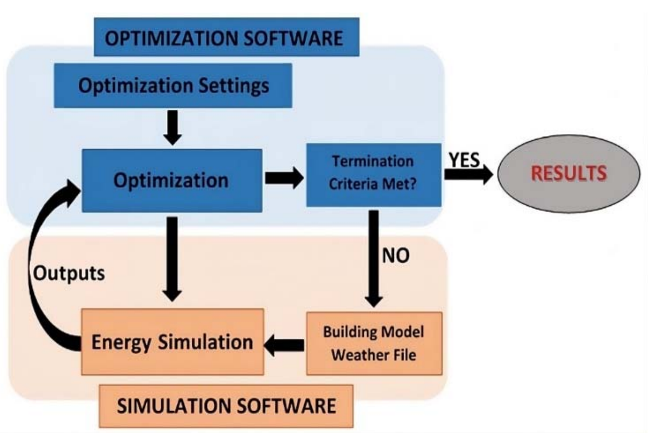

Figure 1. General strategy for building energy optimization.

RESEARCH BACKGROUND

In the architecture, engineering, and construction industry, designers are critical members who make decisions associated with building energy performance. They mostly benefit from parametric trial and error methods to identify the most energy-efficient design alternatives. Nonetheless, passive trial and error methods have been proved ineffective and more time-consuming than simulation-based optimization methods (Wang et al., 2023). Therefore, researchers have recently proposed the use of simulation-based building optimization tools consisting of building simulation and search tools (Sharif and Hammad, 2019).

The most common technique used to develop a building energy optimization system is to integrate numerical simulations and search algorithms (Huang and Niu, 2016; Barber and Krarti, 2022). Researchers have focused on single- and multi-objective design problems with multiple constraints, considering all design parameters that influence building energy performance. They have developed simulation-based optimization systems integrated with search algorithms such as ant colony optimization (Bamdad et al., 2017; Anupong et al., 2023; Khan et al., 2023), grey wolf optimizer (Ghalambaz et al., 2021; Li et al., 2021), particle swarm optimization (Delgarm et al., 2016; Zhou et al., 2020), simulated annealing (Junghans and Darde, 2015; Kheiri, 2021), and genetic algorithm (Ascione et al., 2015; Niemelä et al., 2016; Ascione et al., 2017; Gilles et al., 2017; Al-Saadi and Al-Jabri, 2020).

The integrated systems have been developed using generic platforms and optimization software such as MATLAB, GenOpt, and CAMOS (Bigot et al., 2013; Perera et al., 2016; Li et al., 2020; Ucar, 2024). The search algorithm tools have been coupled with energy simulation software like EnergyPlus, TRNSYS, and DOE-2 to conduct the simulation process (Asadi et al., 2012; Ferrara et al., 2014; Ascione et al., 2016). The developed simulation-based optimization system has been used to optimize thermal comfort (Yu et al., 2016; Naderi et al., 2020; Yue et al., 2021), building envelope and geometry (Song et al., 2017; Yigit and Ozorhon, 2018; Zhou et al., 2018; Caglayan et al., 2020b; Ozel, 2022), insulation thickness (Jin et al., 2017; Ghafoori and Abdallah, 2022), and energy consumption (Griego et al., 2015; Eskander et al., 2017; Ge et al., 2018; Lin and Yang, 2018; Ren et al., 2018; Yigit and Ozorhon, 2018; Lee et al., 2019).

The majority of the studies have targeted optimizing the whole building energy performance, while a limited number of studies have observed the situation for certain building units and rooms (Yu et al., 2008; Kontoleon and Eumorfopoulou, 2010). The apartment units on different floors and orientations may show notably different energy performances. Even though whole building energy optimization is effective in reducing total energy consumption, it ignores the fact that varying energy performance across different units can lead to discomfort among occupants. The problem might be addressed by using a detailed optimization process with a large number of variables. However, energy optimization processes already take quite some time, and the increasing number of variables would make the processes unmanageable.

This study proposes simple optimization approaches that balance the performance variance within units and thus tip the scales in favor of the underperforming apartment units. In this regard, the thermal design of a typical five-story residential building was determined using three different unit-based optimization approaches. The first approach was the conventional optimization approach with the sole objective of minimizing total energy consumption. The variance in the energy performances of different units was observed. Two additional approaches, aiming to minimize both total energy consumption and variance across the units, were introduced. The results of the three approaches were compared to identify the most appropriate approach.

RESEARCH METHODOLOGY

The flowchart of methodology is presented in Figure 2. The methodology is composed of three main stages. The conventional single-phase single-objective optimization was conducted in the first stage to observe the variance in the annual energy requirements of different units. The optimization process focused solely on the minimization of the total building energy consumption with a budget constraint of 50,000 USD. The thermal performance of each unit was investigated and the variance across the units was observed.

In the second stage, in an attempt to balance the variance in the thermal performances of different units, two optimization approaches were proposed: (i) single-phase multi-objective optimization and (ii) multi-phase single-objective optimization. The former utilized the NSGA-II (Non-Dominated Sorting Genetic Algorithm II) technique to minimize both total energy consumption and variance across the units within a budget of 50,000 USD. The latter was a two-phase optimization process, where total energy consumption was minimized by using 90% of the budget (45,000 USD) in the first phase, and the remaining 10% budget (5,000 USD) was used to manually enhance the thermal properties of certain parts in the second phase.

The results of the proposed approaches were compared in the last stage of the methodology. The decision variables resulting in the optimum value were revealed, the annual heating/cooling energy requirements were calculated, and the variances across the units were evaluated. The simulation tool (Energy Plus) was coupled with the optimization tool (DEAP) for the execution of the process in all three approaches (Fortin et al., 2012). Energy Plus was used to calculate the annual energy requirement of the building while DEAP was utilized for the optimization purposes. Python programming language was used to provide the integration between them.

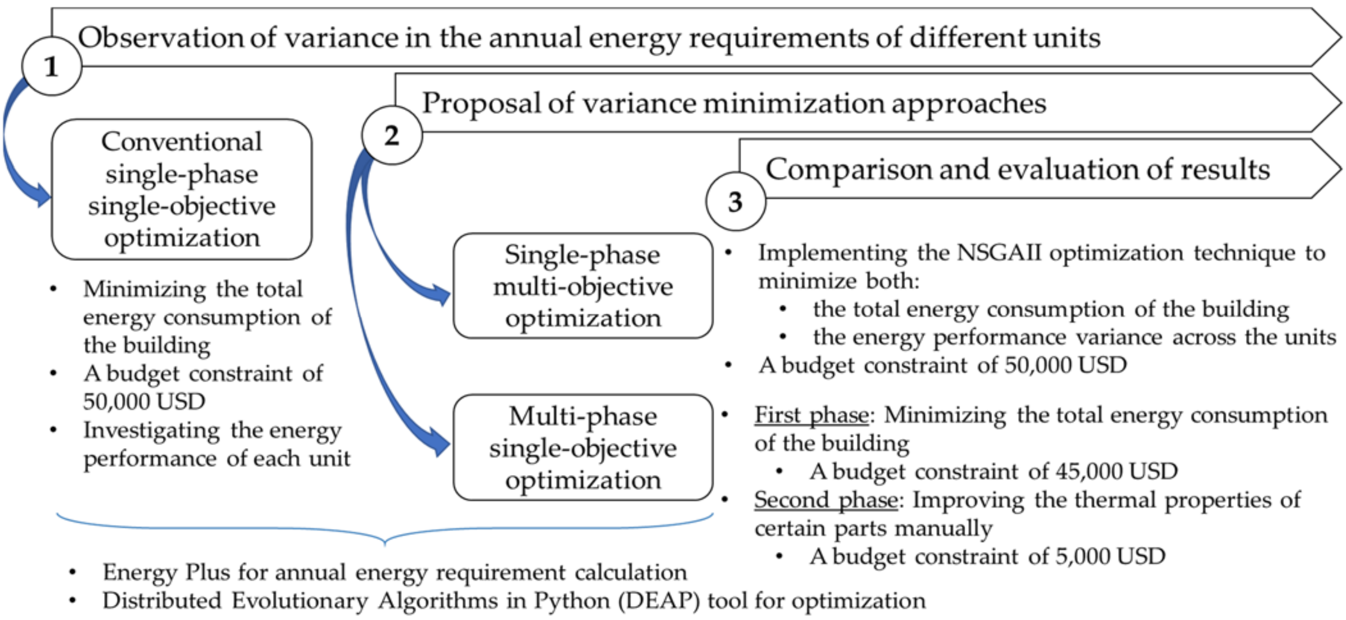

Figure 2. The flowchart of methodology.

Execution of the Optimization Process

The NSGA-II optimization process is presented in Figure 3. The process commences by generating a random population of building designs, with each design represented by a unique combination of parameters related to the building envelope. These parameters include insulation thickness and window-to-wall ratio, among others. Each building configuration in this population undergoes evaluation through simulation using EnergyPlus, automated by a Python script developed by the authors. Following simulation, the energy performance of each building design is assessed based on energy consumption.

The optimization process iterates until termination criteria are satisfied, signaling either the achievement of desired energy performance or reaching a predefined limit on the number of iterations. To evolve the population towards improved solutions, genetic operations including selection, mutation, and crossover are applied. Selection favors individuals with higher fitness (i.e., better energy performance), while mutation introduces random changes to foster exploration of new design spaces. Crossover facilitates the exchange of genetic material between selected individuals, generating offspring with combined features from parent designs. Through this repetitive process of simulation, evaluation and refinement, the optimization algorithm progressively improves the population, eventually converging towards building designs that exhibit higher energy performance. This methodology offers a systematic approach to addressing the complex design space of building envelopes and outputs near-optimal/Pareto-optimal results in the end.

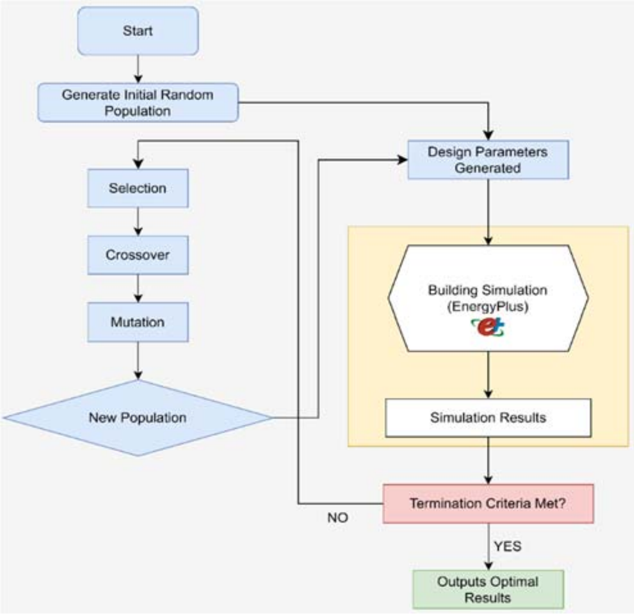

Figure 3. NSGA-II optimization process.

Characteristics of the Reference Building

A typical five-story residential building was selected as the reference building. The architectural plan and side view of the building are shown in Figure 4. The building had a footprint area of 600 m². Each floor had six units of equal sizes, and the height was 3 m. The window-to-wall ratios of the east, west, north, and south facades were set as variables to be optimized. The ranges of these variables are expressed in the section called settings and design parameters.

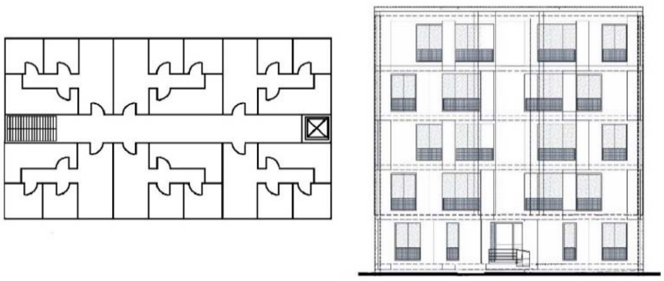

Figure 4. Architectural plan and side view of the residential building.

The simplified model of the building is presented in Figure 5. The building had a total of 30 apartment units. To observe the variance in the energy performance of different units, the model created in EnergyPlus was composed of 30 different zones. The building was cooled above 24°C and heated below 20°C. The orientation of the building was fixed due to land constraints in urbanized areas, and the building was oriented to the North.

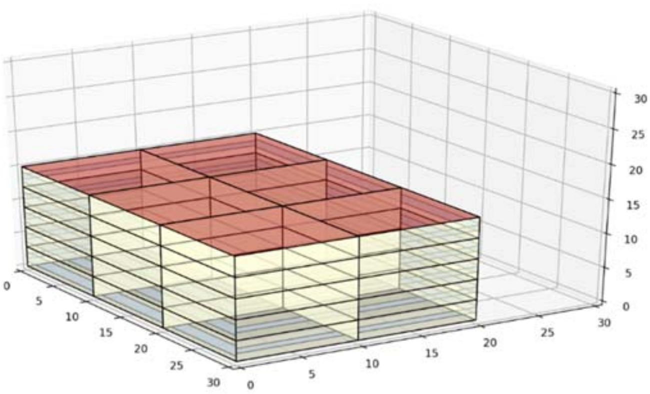

Figure 5. Simplified 3D model of the building.

Energy Efficiency Measures

An extended market investigation was conducted to determine the energy efficiency measures for the reference building. A variety of construction materials is available in the market, but contractors mainly prefer certain types of materials due to their functionality and cost-effectiveness. Expanded polystyrene (EPS) is the most popular insulation material applied to the exterior walls. Extruded polystyrene (XPS), on the other hand, is mostly preferred for the basement and roof due to its greater compressive strength. The thicknesses of the insulation materials are the variables to be optimized. Double-glazed PVC frames are widely used for windows in the market. Therefore, the building envelope was designed with the most commonly used construction materials. The cross-sectional details of the building envelope components are presented in Table 1.

Table 1. Cross-sectional details of the building envelope.

Component	*Cross-sectional elements*	*Thickness*
Basement	Acoustic tile	2 cm
	XPS (to be optimized)	2 – 15 cm
	Heavy weight concrete	12 cm
Roof	Slag or stone	2 cm
	Felt and membrane	1 mm
	XPS (to be optimized)	2 – 15 cm
	Heavy weight concrete	12 cm
Interior slabs	Acoustic tile	2 cm
	Heavy weight concrete	12 cm
Exterior walls	Dense face brick	10 cm
	EPS (to be optimized)	2 – 15 cm
	Light weight concrete	5 cm
	Plaster or gyp board	2 cm
Interior walls	Plaster or gyp board	2 cm
	Dense face brick	10 cm
	Plaster or gyp board	2 cm
Windows	PVC frame double glazed	16 mm

Locations and Meteorological Data

The optimization process was repeated for three cities representing different climate conditions of Türkiye. These three regions were selected based upon their climate conditions and urbanization levels. Ankara, Istanbul, and Izmir are the most urbanized cities of Türkiye and the majority of the population in Türkiye is concentrated in these cities.

The geographic properties and climate conditions of these cities are presented in Table 2. The cities are located at latitudes between 30° and 40° and longitudes between 27° and 33°. The time zone in all three cities is +2. Ankara is situated at a considerably higher elevation. The climate of Ankara is characterized as continental Mediterranean, featuring hot-dry summers and cold winters. The climate in Istanbul is transitional Mediterranean, which implies hot-humid summers and cold winters. The climate of Izmir is classified as Mediterranean, with hot-dry summers and mild winters.

Table 2. Geographic properties and climate conditions of Ankara, Istanbul, and Izmir.

	Ankara	*Istanbul*	*Izmir*
Latitude	40.12	30.97	38.50
Longitude	32.98	28.82	27.02
Time zone	+2	+2	+2
Elevation	949.00 m	37.00 m	5.00 m
Climate	Continental Mediterranean	Transitional Mediterranean	Mediterranean

The weather data for Ankara, Istanbul, and Izmir were obtained from the official website of EnergyPlus (EnergyPlus, 2020). The average and standard deviation of temperature and relative humidity ratio for each city are presented in Table 3. The average temperature ranges between -1.32°C and 20.68°C, 5.38°C and 23.10°C, and 8.60°C and 24.64°C in Ankara, Istanbul, and Izmir, respectively. Similarly, the relative humidity ratio ranges between 46.79% and 80.79%, 64.54% and 82.75%, and 49.50% and 80.79% in Ankara, Istanbul, and Izmir, respectively. The optimization process also considered the standard deviations in the analyses.

Settings and Design Parameters

The settings of the genetic algorithm radically influence the probability of obtaining the optimal solution, as the number of iterations and population diversity are defined by these parameters. However, no mathematical formula has been suggested for the accurate calculation of these parameters. Instead, the parameters are mostly determined based on a rule of thumb depending on the complexity of the problem or through trial-and-error methods for each optimization problem. The settings determined after iterative runs are presented in Table 4.

In configuring the genetic algorithm for optimization, a group of 30 potential solutions was preferred, referred to as the population. The algorithm was allowed to iterate 50 times, expecting its ability to locate the most favorable solution(s). To add variety to the solutions, the solutions were permitted to exchange certain characteristics (crossover) 80% of the time. Additionally, each solution had a 5% chance of independently undergoing slight changes (mutation) to maintain diversity. The selected crossover and mutation methods are particularly suitable for problems involving continuous variables. Utilizing the non-domination sorting method enabled the identification of top solutions and ensured the exploration of diverse possibilities. The algorithm was concluded after 50 repetitions to conserve computational resources.

The number and ranges of the decision variables should be carefully determined to identify the energy-optimal building design. They should allow for the consideration of all possible options in the optimization process. On the other hand, they should be determined so that the optimization problem becomes manageable, and the calculations are completed within a reasonable time period. It has already been mentioned that the orientation and gross floor area were kept fixed due to land constraints and dense urbanization. The window-to-wall ratios of the façades, solar absorption values of the roof and exterior walls, and insulation thicknesses of the basement, exterior walls, and roof were selected as the decision variables to be optimized. The design parameters and their ranges are presented in Table 5.

Table 3. Weather data used in the optimization process.

Months	*Ankara*				*Istanbul*				*Izmir*			
	Temp (°C)		*Relative Humidity (%)*		*Temp. (°C)*		*Relative Humidity (%)*		*Temp. (°C)*		*Relative Humidity (%)*	
	Avg.	*Std.*	*Avg.*	*Std.*	*Avg.*	*Std.*	*Avg.*	*Std.*	*Avg.*	*Std.*	*Avg.*	*Std.*
January	-1.32	4.59	78.67	8.02	6.20	1.99	78.71	3.84	9.10	2.05	80.79	5.99
February	1.39	3.99	67.46	9.20	5.38	2.28	68.58	4.91	8.60	2.36	71.17	6.78
March	3.20	4.09	65.29	11.74	7.50	2.07	75.50	5.98	10.65	3.15	73.08	9.01
April	9.04	3.74	65.79	12.69	12.08	2.53	66.67	7.42	14.07	3.21	71.04	8.86
May	13.39	4.66	64.13	15.85	16.25	3.03	72.46	6.86	20.13	5.04	58.58	12.66
June	16.46	5.45	56.63	16.57	20.72	4.08	64.54	8.86	23.33	6.11	55.00	13.98
July	20.68	5.47	48.42	13.29	23.04	4.63	70.58	13.05	24.64	6.03	49.50	11.48
August	20.22	5.77	46.79	13.28	23.10	4.70	74.63	9.44	24.16	6.07	57.79	12.56
September	16.52	5.53	56.04	19.03	19.99	3.91	66.00	12.46	22.02	5.62	58.79	13.26
October	10.28	3.87	62.96	12.66	15.97	2.87	70.08	11.19	16.42	3.94	65.04	11.02
November	4.24	3.16	71.83	8.36	11.24	1.71	74.92	5.34	11.30	3.19	66.50	9.27
December	1.60	3.46	80.79	6.81	8.11	1.40	82.75	3.22	9.89	1.92	73.38	6.00

Table 4. Settings of the genetic algorithm optimization.

Parameter	*Value*
Population size	30
Number of generations	50
Crossover rate	0.8
Mutation rate	0.05
Crossover	Simulated binary bounded
Selection	Non-domination rank
Mutation	Polynomial bounded
Termination	Maximum generation

Table 5. Optimization design parameters.

Parameter	*Component*	*Lower Bound*	*Upper Bound*
Window-to-wall ratio	North façade	0.3	0.9
	South façade	0.3	0.9
	East façade	0.3	0.9
	West façade	0.3	0.9
Solar absorption	Roof	0.3	0.8
	Exterior walls	0.3	0.8
Insulation thickness	Roof	2 cm	15 cm
	Exterior walls	2 cm	15 cm
	Basement	2 cm	15 cm

Characteristics of the Optimization Approaches

This study has introduced three different approaches to investigate the energy performance of the apartment units for three different climate conditions. The characteristics of these approaches are summarized in Table 6. The first approach is the conventional single-phase single-objective optimization, which focuses only on the total energy consumption of the building. It attempts to find the optimal design within a budget constraint of 50,000 USD and does not consider the variation of the performance across the units. The second approach is a single-phase multi-objective optimization, which utilizes the NSGA-II optimization technique to minimize both the total energy consumption and variance within the units. The approach uses the same amount of budget. The third approach is a multi-phase single-objective optimization, which attempts to minimize the total energy consumption in the first phase and varying performance of different units in the second phase. The approach uses 90% of the budget (45,000 USD) in the first phase to minimize the whole building energy consumption, and the remaining 10%

of the budget (5,000 USD) is used in the second phase to manually improve the thermal properties of certain parts.

Table 6. The characteristics of the introduced approaches.

Approach	*Budget Constraint*	*Characteristics*
Single-phase single-objective optimization	50,000 USD	The conventional approach attempting to minimize solely the total energy consumption of the building
Single-phase multi-objective optimization	50,000 USD	The approach attempting to minimize both (i) the total energy consumption and (ii) variance within the apartment units
Multi-phase single-objective optimization	Phase I: 45,000 USD Phase II: 5,000 USD	The approach attempting the minimize the total energy consumption in the first phase and variance within the units in the second phase

RESEARCH RESULTS AND DISCUSSION

Single-Phase Single-Objective Optimization

The reference building design was optimized in three different climate conditions with the aim of minimizing the energy demand of the building. The purpose of these runs is to investigate the performance variance between the housing units of an energy-optimized residential building. Additionally, these runs demonstrate the effectiveness of conventional optimization methods in balancing the energy performance of each apartment unit. The upper and lower boundaries of the parameters are presented in Table 5. The convergence of the optimization process is shown in Figure 6.

The building design parameters obtained from the optimization process are presented in Table 7. Despite the varying climate conditions of Ankara, Istanbul, and Izmir, the energy-optimal design parameters selected by the genetic algorithm optimization tool were quite similar. The window-to-wall ratios were higher on the north façade. The solar absorption values of the exterior walls were greater than those of the roofs (except for Izmir). The insulation thicknesses were greatest in the exterior walls, followed by the roof and basement.

The optimal design configurations were simulated in the EnergyPlus energy simulation software. The heating and cooling loads of the building located in Ankara were obtained as 118,345 kWh and 64,308 kWh, respectively. The total energy consumption of the units ranged between 2,800 kWh and 10,978 kWh, with a standard deviation of 2,299 kWh. The heating load of the building located in Istanbul was 66,700 kWh, and the cooling load was 103,807 kWh. The total energy consumption of the units varied between 2,502 kWh and 9,285 kWh, with a standard deviation of 1,938 kWh. The building located in Izmir had heating and cooling loads of 27,260 kWh and 138,048 kWh, respectively. The total energy consumption of the units ranged between 2,342 kWh and 8,582 kWh, with a standard deviation of 1,834 kWh. As expected, the building located in Izmir had the highest cooling loads, while the building located in Ankara had the highest heating loads. The energy consumptions of each unit are demonstrated in Figure 7. Sections A, B, C, D, E, and F represent the northwest, north, northeast, southwest, south, and southeast corner units, respectively. In the next sections, the proposed variance minimization approaches are implemented to reduce the performance differences across the units.

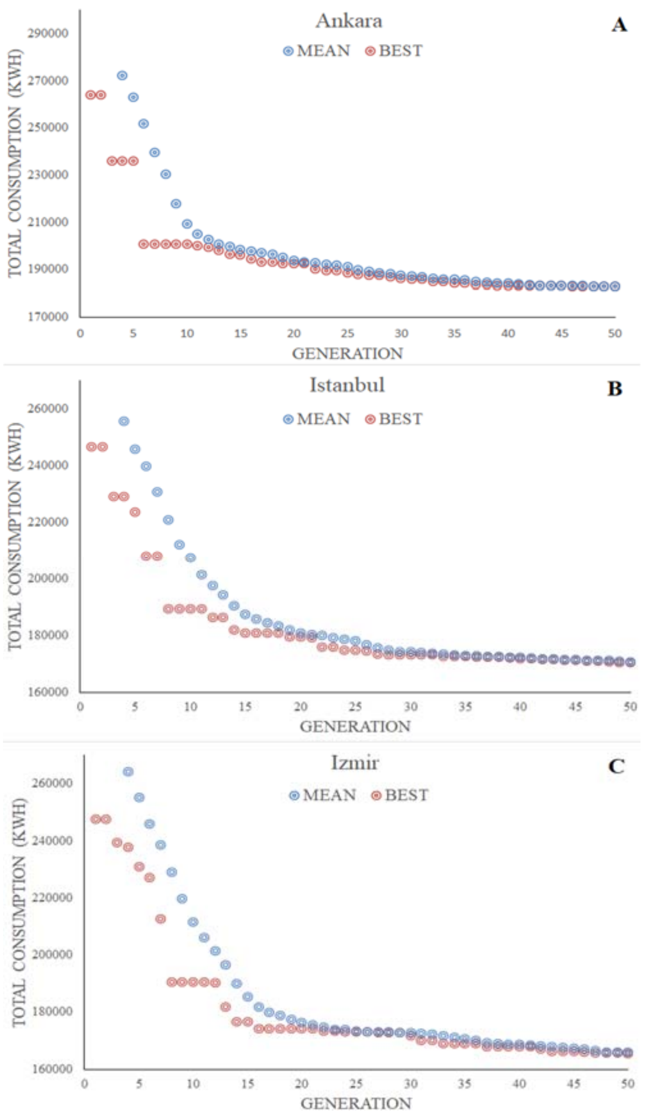

Figure 6. The convergence of the single-phase single-objective optimization process.

Table 7. Optimal design parameters for the single-phase single-objective optimization approach.

Parameter	*Component*	*Ankara*	*Istanbul*	*Izmir*
Window-to-wall ratio	North façade	0.381	0.328	0.315
	South façade	0.311	0.303	0.305
	East façade	0.301	0.301	0.300
	West façade	0.300	0.317	0.304
Solar absorption	Roof	0.313	0.312	0.662
	Ext. walls	0.537	0.589	0.324
Insulation thickness	Ext. walls	14.9 cm	13.6 cm	14.6 cm
	Roof	9.2 cm	8.7 cm	9.6 cm
	Basement	2 cm	4.4 cm	2.3 cm

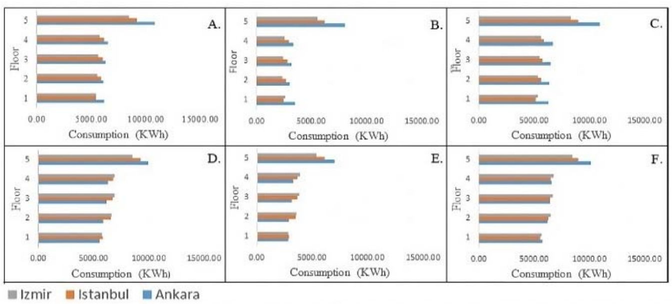

Figure 7. Simulation results of the single-phase single-objective optimization approach.

Single-Phase Multi-Objective Optimization

The single-phase multi-objective optimization approach was conducted to minimize both the total energy consumption and variance within the units. An NSGA-II optimization methodology was implemented to carry out the optimization process in three different climate conditions. The aim of these runs was to investigate the effectiveness of the proposed approach in reducing the energy performance variance within the units and providing a more balanced energy demand profile. A large number of test runs were conducted to find optimal generation numbers and population size. The test runs demonstrated that although increasing these parameters could provide slightly better results, the optimization time periods were greatly increased. Therefore, the parameters such as the number of generations, population size, and offspring size were kept constant to obtain results in a reasonable time period. The upper and lower boundaries of the parameters are presented in Table 5. The results of the optimization process are presented in Figure 8.

The building design parameters obtained from the single-phase multi-objective optimization process are presented in Table 8. The window-to-wall ratios were almost similar except for the south façade of the building in Ankara. The solar absorption values of the exterior walls were greater than those of the roofs. The solar absorption values were slightly greater in Ankara than in Istanbul and Izmir. The insulation thicknesses of the basement were considerably less than those of the roof and exterior walls.

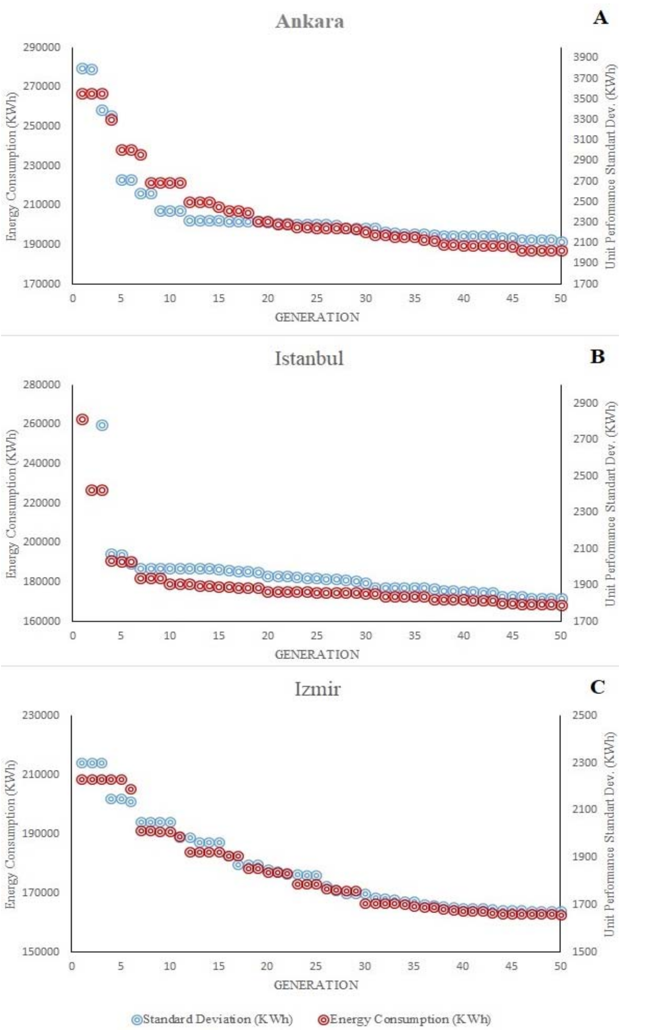

Figure 8. The convergence of the single-phase multi-objective optimization process.

The optimal design configurations obtained from the single-phase multi-objective optimization approach were simulated in EnergyPlus software. The heating and cooling loads of the building located in Ankara were 120,485 kWh and 66,346 kWh, respectively. The total energy consumption of units ranged between 2,928 kWh and 10,432 kWh, with a standard deviation of 2,126 kWh. The heating load for the building located in Istanbul was 68,293 kWh, and the cooling load was 96,900 kWh. The total energy consumption of the units varied between 2,485 kWh and 9,042 kWh, with a standard deviation of 1,879 kWh. The building located in Izmir had heating and cooling loads of 29,134 kWh and 133,306 kWh, respectively. The total energy consumption of the units ranged between 2,335 kWh and 8,118 kWh, with a standard deviation of 1,724 kWh. The energy consumptions of each unit are demonstrated in Figure 9. The figure shows that the unit performance of the optimized building located in Ankara was slightly more balanced. The performance variance between the units of the building located in Izmir was significantly reduced, and the total energy performance of the building was increased. The unit performance of the building located in Istanbul was also moderately balanced.

Table 8. Optimal design parameters for the single-phase multi-objective optimization approach.

Parameter	*Component*	*Ankara*	*Istanbul*	*Izmir*
Window-to-wall ratio	North façade	0.312	0.302	0.302
	South façade	0.356	0.301	0.303
	East façade	0.307	0.304	0.300
	West façade	0.301	0.301	0.302
Solar absorption	Roof	0.421	0.301	0.315
	Ext. walls	0.457	0.399	0.375
Insulation thickness	Ext. walls	8.1 cm	12.5 cm	10.7 cm
	Roof	13.8 cm	9.4 cm	10.8 cm
	Basement	4.4 cm	4.7 cm	3.6 cm

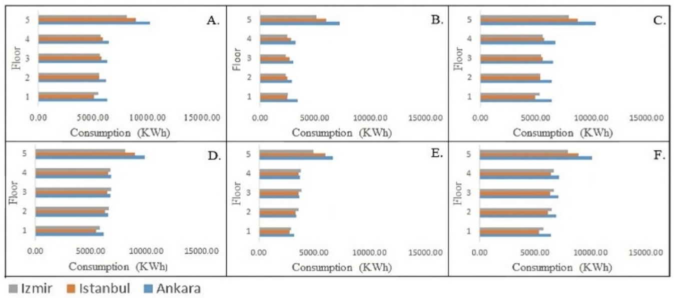

Figure 9. Simulation results of the single-phase multi-objective optimization approach.

Multi-Phase Single-Objective Optimization

The approach is conducted in two phases. In the first phase, a single-objective genetic algorithm optimization was conducted to minimize the total energy demand of the building. The only constraint defined in the optimization process was the budget corresponding to 90% of the total amount (45,000 USD). A small portion of the budget was withheld to be used in the second phase. The aim of the first phase was to obtain an energy-optimized building design, which would be manually adjusted in the next phase. In this way, the designers had the chance to balance the varying energy performance of different units in the second phase by conducting a trial-and-error design process. The parameters of the genetic algorithm were kept constant to obtain results in a reasonable time period. The upper and lower boundaries of the parameters are presented in Table 5. The results of the optimization process are presented in Figure 10.

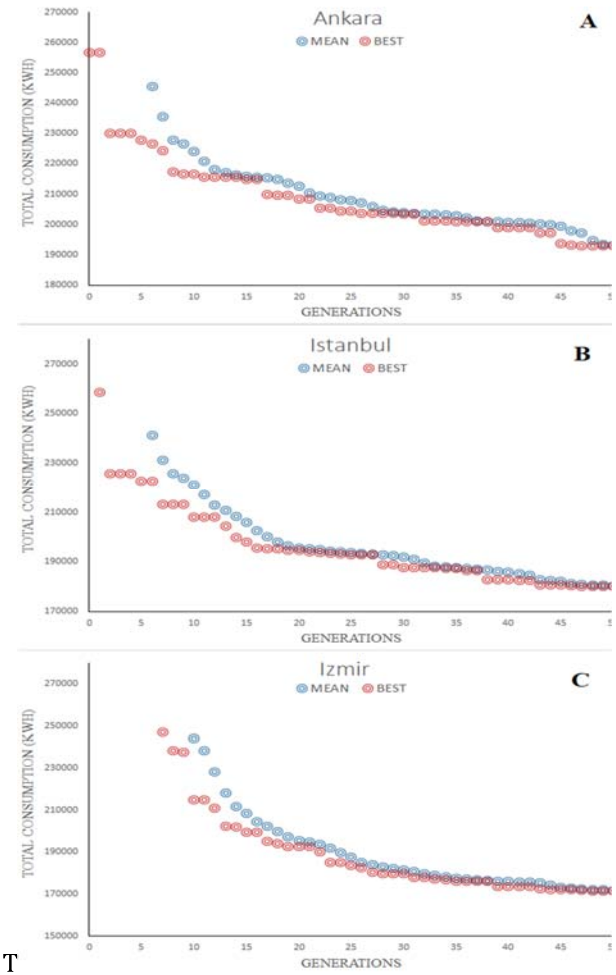

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Figure 10. The convergence of the multi-phase single-objective optimization process.

he building design parameters obtained from the first phase of the multi-phase single-objective optimization process are presented in Table 9. The cost of the obtained design configurations was 45,000 USD. In the second phase, the designer could reduce energy demand and balance the energy performance of each unit with manual adjustments. In the second phase of the approach, a trial-and-error method was implemented to balance the energy performance of the housing units. The results of the previous analyses showed that the top-floor units had the lowest energy performance. Additionally, it was observed that the insulation material used in the basement was not cost-effective. Therefore, in the second phase, the design configuration obtained from the first phase of the optimization process was modified to increase the thermal performance of the top-floor units.

Considering the budget constraints and using the information gained from the previous simulations, the following measures were taken to minimize energy consumption and balance the energy performance of the units:

- Increasing the insulation thickness of the roof,
- Increasing insulation thickness of the top floor exterior walls,
- Adding Low-E glazing to the top floor windows (it is not possible to use Low-E glazing for the whole building due to the high costs),
- Reducing the insulation thickness of the basement to provide additional budget,
- Increasing the insulation thickness of the exterior wall for the whole building if required,
- Reducing the window area of the building to create an extra budget.

The modified building design parameters and the additional design changes obtained from the second phase of the optimization process are presented in Table 10. Low-E glazing was used on the top floor for all three cities. The insulation thickness of the exterior walls was increased to 15 cm on the top floor, but only for the case of Istanbul.

Table 9. Optimal design parameters for the first phase of the multi-phase single-objective optimization approach.

Parameter	*Component*	*Ankara*	*Istanbul*	*Izmir*
Window-to-wall ratio	North façade	0.312	0.300	0.303
	South façade	0.303	0.300	0.301
	East façade	0.303	0.378	0.320
	West façade	0.301	0.302	0.304
Solar absorption	Roof	0.472	0.404	0.304
	Ext. walls	0.397	0.400	0.382
Insulation thickness	Ext. walls	6.2 cm	6.7 cm	7.6 cm
	Roof	9.6 cm	8.7 cm	6.7 cm
	Basement	3.0 cm	4.0 cm	4.7 cm

Table 10. Optimal design parameters for the second phase of the multi-phase single-objective optimization approach.

Parameter	*Component*	*Ankara*	*Istanbul*	*Izmir*
Window-to-wall ratio	North façade	0.300	0.300	0.303
	South façade	0.300	0.300	0.301
	East façade	0.300	0.300	0.300
	West façade	0.300	0.300	0.304
Solar absorption	Roof	0.472	0.404	0.300
	Ext. walls	0.397	0.400	0.300
Insulation thickness	Ext. walls	8.0 cm	11.0 cm	7.6 cm
	Roof	15.0 cm	10.0 cm	15.0 cm
	Basement	2.0 cm	2.0 cm	2.0 cm
Additional modifications on the top floor	Low-E glazing (all three cities) Exterior wall insulation thickness: 15cm (Istanbul)			

The optimal design configurations obtained from the second phase of the multi-phase single-objective optimization process were simulated in the EnergyPlus software. The heating and cooling loads of the building located in Ankara were 116,706 kWh and 58,379 kWh, respectively. The total energy consumption of each unit ranged between 2,883 kWh and 9,295 kWh, with a standard deviation of 1,869 kWh. The heating load for the building located in Istanbul was 65,501 kWh, and the cooling load was 96,661 kWh. The total energy consumption of each unit varied between 2,503 kWh and 8,496 kWh, with a standard deviation of 1,717 kWh. The building located in Izmir had heating and cooling loads of 28,997 kWh and 131,927 kWh, respectively. The total energy consumption of each unit ranged between 2,419 kWh and 7,757 kWh, with a standard deviation of 1,627 kWh. The energy consumptions of each unit are demonstrated in Figure 11. The figure shows that the unit performances of the optimized design were more balanced compared to the unit performances in the other approaches. Additionally, in some cases, the total energy demands of the buildings were also lower compared to the other design solutions.

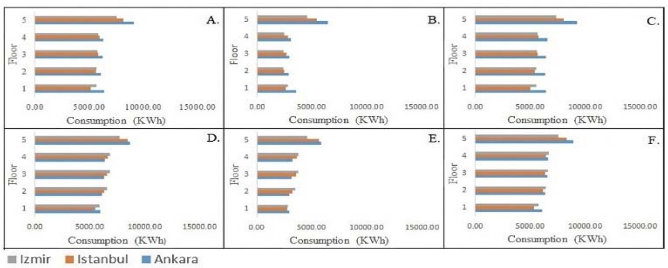

Figure 11. Simulation results of the multi-phase single-objective optimization approach.

Evaluation of the Results

Table 11 summarizes the results obtained from the three optimization approaches. The results of the first approach demonstrated that designing the building envelope based on the conventional single-phase single-objective optimization produced a design with imbalanced thermal performance. The top floor units and corner units performed poorly, while comparatively better performances were observed in the other units. Although the total energy was reduced, a remarkable performance difference was observed among the units.

Table 11. The summary of the results.

Approach	*Location*	*Heating (kWh)*	*Cooling (kWh)*	*Min-Max Range (kWh)*	*Std. Dev. (kWh)*
Single-phase single-objective optimization	Ankara	118,345	64,308	2,800-10,978	2,299
	Istanbul	66,700	103,807	2,502-9,285	1,938
	Izmir	27,260	138,048	2342-8,582	1,834
Single-phase multi-objective optimization	Ankara	120,485	66,346	2,928-10,432	2,126
	Istanbul	68,293	96,900	2485-9,042	1,879
	Izmir	29,134	133,306	2,335-8,118	1724
Multi-phase single-objective optimization	Ankara	116,706	58,379	2,883-9,295	1,869
	Istanbul	65,501	96,661	2,503-8,496	1,717
	Izmir	28,997	131,927	2,419-7,757	1,627

The imbalanced thermal performance obtained from the conventional optimization approach necessitated the introduction of optimization approaches focusing on balancing the energy performance of the apartment units and minimizing the total energy demand of the building. The introduced methodologies were tested, and the results indicated that both methods could be useful in providing designs with balanced thermal performance. The multi-phase single-objective optimization approach resulted in slightly better outputs compared to other approaches. It provided more balanced unit performances and also reduced the total energy consumption of the building by 3–5%.

The performance difference between the top floor and other floors was significantly diminished with the implementation of the introduced unit-based optimization approaches. The difference between the middle and corner units could not be reduced due to the building geometry. The corner units, by their nature, have two external surfaces and a larger area of window surface compared to middle units. Thus, they require more energy to maintain acceptable thermal comfort. The trial-and-error analyses in the multi-phase single-objective optimization also confirmed that balancing the energy performance of the middle and corner units was not cost-effective and reduced the total energy performance of the building.

The study aimed to optimize the envelope design of a typical five-story residential building and examined the performances of three different optimization approaches with single/multi-phase and single/multi-objective objectives. Even though multi-phase and multi-objective optimization approaches have been employed in a number of studies for thermal design improvement (Kim and Clayton, 2020; Wang et al., 2020; Ciardiello et al., 2020), none of the studies have considered the varying energy performance across different units and compared the capabilities of different approaches to obtain the desired outcome. The proposed approaches enabled the execution of unit-based optimization techniques that can overcome the imbalanced thermal performance phenomenon. In that sense, the study presents pioneering research in the field of thermal design optimization.

CONCLUSIONS

Governmental regulations and climate changes have compelled designers to construct energy-efficient buildings. Simulation-based optimization approaches have proven effective methods in finding energy-efficient building designs. Designers commonly use energy optimization approaches to minimize the total building energy demand. They should also consider the performance variance within the apartment units. For this purpose, three different optimization approaches were analyzed in three different climate conditions to observe the performance difference and evaluate the results of the introduced optimization approaches.

The results of the conventional optimization approach pointed out a significant thermal performance imbalance among the units. The approach was implemented solely to minimize the energy consumption of the building. It was also observed that the performance difference between the housing units couldn't be reduced to a considerable level without increasing the number of design parameters. The increasing number of design parameters eventually reduced the manageability of the problem and greatly increased the optimization periods. The optimization periods of the conventional optimization approach were already beyond the acceptable level. Thus, increasing optimization periods would significantly impact the practicality and usability of the approach.

The proposed approaches were tested in the second and third case runs. The results indicated that both approaches could diminish the varying energy performance within the units. The single-phase multi-objective optimization approach was easy to implement and required no extra pre-process and post-process work. Therefore, it can easily be integrated into the daily work of a designer. On the other hand, even though the multi-phase single-objective optimization approach required post-process work, it resulted in better outputs. In the second phase, the designers were able to evaluate and modify the thermal performance of the building without any parameter limit. The proposed approaches increased the performance of the underperforming units and decreased the total energy demand. The results showed that the proposed methodologies were easy to implement, effective, and could be used to optimize the building thermal design.

The study contributes to the literature by addressing a common but largely neglected problem for the thermal design of residential buildings and proposing a couple of unit-based optimization approaches that take the issue into account. The study is expected to raise awareness among design professionals and companies about the varying thermal performance within the units. The study has also demonstrated that conventional optimization approaches could have difficulty overcoming the problem, and thus, design professionals and companies should become familiar with the proposed unit-based optimization approaches to design convenient buildings.

The proposed optimization approaches were performed for a frequently used five-story residential building design. The findings might be subjected to changes for buildings with different geometries, which can be regarded as a limitation. Further studies may focus on repeating the methodology for other building types and revealing the differences in the findings. Moreover, the analyses included the climate properties of the most popular and crowded three cities in Turkey, namely Ankara (continental Mediterranean), Istanbul (transitional Mediterranean), and Izmir (Mediterranean). Prospective studies should involve other climate types to obtain universal results.

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