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SR. NO.	P A R T I C U L A R	PAGE NO.	DOI NUMBER
1.	**SHOCKS AND STABILITY: ASSESSING ECONOMIC RESILIENCE THROUGH CAPITAL EXPENDITURE IN INDIAN STATES** Naresh Kumar, Kamal Singh	1-20	10.5958/2278-4853.2026.00035.2
2.	**AN ARTIFICIAL NEURAL NETWORK-ASSISTED ZERO-RIPPLE HIGH-GAIN POWER INTERFACE FOR PHOTOVOLTAIC DC MICROGRIDS** Kaladeepan R, Dr.R.Suja Mani Malar	21-30	10.5958/2278-4853.2026.00036.4

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SHOCKS AND STABILITY: ASSESSING ECONOMIC RESILIENCE THROUGH CAPITAL EXPENDITURE IN INDIAN STATES

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ABSTRACT:

This study is based on the theoretical framework of endogenous growth theory. Using a difference-in-difference (did) estimation technique applied at the state-level over time before and after COVID-19, this study investigates how different levels of capital expenditures prior to the pandemic affect subsequent post-pandemic economic resilience. States with higher pre-pandemic capital expenditures were found to have had 4.4 percent more growth in their per capita gross state domestic product (GSDP) during the post-pandemic period. These results highlight the role of government spending in facilitating economic recovery. In addition, sectoral differences in contributions to state level economic resilience among used variables showed that agriculture was the largest contributor followed closely by manufacturing and then construction. Additionally, the results provide specific recommendations to policymakers regarding implementing infrastructure investments, providing expanded financial access and developing inclusive growth strategies to achieve long run stability in state economies.

KEYWORDS: *Government Expenditure, Economic Growth, External Shocks, Economic Resilience.*
JEL Codes: C19, E69, H12, H72

1. Introduction and Theoretical-Empirical Background

Increasing the economic growth has been a principal objective of those in power and economists as well. It means higher output of what a nation is capable of producing and the lifestyle of its citizens is enhanced. Theories of economic growth have long since their early days of classic ideas of Adam Smith and David Ricardo. We can now have more current opinions, including the growth model of Solow and the endogenous growth theory (Solow, 1956; Romer, 1990; Barro and Sala-i-Martin, 2004). These concepts bring to the fore such things as the need to save up money, new technology and the skills of workers as the key to making an economy grow over

time. The recent research has extended the debate further to include the way in which such factors as the presence of an efficient financial system, the availability of talent, good health, a strong institutional system and a good steward of the environment all influence the degree to which an economy will grow.

It has been observed that the presence of skilled labor force and good governments are very crucial to sustainable economic development. Barro (2013) indicated that quality of education is more relevant than simply having a lot of it, particularly in the still developing countries. Ghosh (2006) examined the extent to which the people in various regions of India were doing well and concluded that simply because the economy is performing well, it did not automatically imply that the people in different regions of India were achieving well in life. He proposed to concentrate on investing in people. Wang et al. (2022) emphasized that in cases when the government and private companies collaborate and invest in infrastructure, it actually benefits the economy of those regions to grow better. Coad et al. (2022) investigated what companies in Europe hoped to invest after COVID-19 and discovered that a lack of enough money was a significant issue towards getting the economy back on track.

The link between being healthy and doing well economically has also gotten a lot of attention. Studies by Bhargava et al. (2001) and Rivera and Currais (1999) showed that when people are healthier, they are more productive, which leads to the economy growing steadily. Gupta and Mitra (2004) built on this by showing that spending money on healthcare in India not only helps the economy grow but also reduces poverty. How well institutions are run and political factors also have a big impact on the economy. Liu et al. (2018) emphasized that having good governance helps the economy be more resilient, with changes to how institutions work being key to long-term growth. Similarly, Wahiba and Weriemmi (2014) argued that when there's a big gap between the rich and poor, it can hold back the economy in the long run, highlighting the need for growth that benefits everyone.

Although the above studies have helped us in gaining a better insight into what drives long-term economic growth, it is important to keep in mind that a higher level of growth does not necessarily translate into a more resilient economy. Economic resilience is all about how an economy is able to weather the storms, bounce back when it is hit as well as adjusting to new realities. And all without compromising on the long-term growth potential. Economic development does not occur in a linear manner. There are often unforeseen challenges to the economy such as financial crisis, pandemics and geopolitical events which really test their resilience. Resilience could be divided into two broad categories: absorptive capacity, which enables reduction of short-term economic losses and adaptive capacity, which allows long-term structural adjustments. Other past studies have indicated various factors that contribute to economic resilience, such as things like public investment, strong institutions, diverse industries and effective government policies (Rose, 2007; Simmie and Martin, 2010; Briguglio et al., 2014; Duval et al., 2020). As an example, analyses of the global financial crisis of 2008 revealed that those economies with healthy financial reserves and mixed-industry recover faster than those that have overly dependent on a specific sector (Ortiz and Cummins, 2013; Chen et al., 2019; Yu and Kim, 2021). Likewise, the studies of the COVID-19 pandemic have emphasized the role of factors such as strong health care systems, social safety nets and digital technology in mitigating the impact on the economies (Abdoul-Azize and El Gamil, 2021; Abidi et al., 2023; Mohamed, 2023; Yimga, 2024).Developing on this, a series of studies have examined how economies can cope and recover following crises both on a big-picture, macro-level scale and on a sector-

specific level, which contributes towards resilience. An example is an analysis by Briguglio and Piccinino (2012) on how East Asia responded to the 2008-2009 global recession and the significance of macroeconomic stability, investment and flexible markets in making the economies stronger. In a study of transition economies, Filipović and Miljkovic (2014) used a statistical method known as difference-in-differences (DiD) to determine the relationship between the number of market reforms and the country's developmental performance. In a similar investigation, Liu et al. (2018) revealed that good governance enhances efficiency of institutions and red tape, which consequently contributes to resilient economic performance.

Another important factor of resilience has also been identified as performance of certain sectors. Islam et al. (2020) and Chakraborty and Nunnenkamp (2008) studied the role of agriculture and manufacturing, where agriculture has been shown to be more important in Bangladesh, compared to manufacturing which has been found to be more vital to sustain the growth of India. Singh (2016) also stressed the need to have balanced relations between the various sectors in India and how the co-ordinated growth of the various sectors contributes to stability and sustainability. Recent studies have further enlightened us about economic resilience by examining fiscal, structural and sustainability features. In India, a number of studies point out how intense the COVID-19 shock was and how it impacted the economy via a number of channels. The article by Barbate et al. (2021) reveals that the pandemic led to a steep decline, in the economic activity by disrupting the supply and demand. Conversely, Patnaik and Sengupta (2020) show that financial pressures and declining revenues had a big impact on preventing the government to use fiscal policy to stimulate the economy. Likewise, Ramakumar and Kanitkar (2021) point out that the weak fiscal response on the demand side, as well as existing structural weaknesses, diminished the ability of the economy to recover fast. Notably, the evidence available in terms of the state-level analysis indicates that there are truly significant disparities in economic outcomes across regions as they are conditioned by differences in infrastructure, governance and economic structure (Deb and Xu, 2021).

Going beyond the acute crisis, recent research also points to the importance of structural and institutional factors in determining long-term resilience. As an illustration, Mehroush et al. (2024) and Ullah and Shaheen (2024) show that the relationship between financial growth, technological innovations and the quality of governance and policy frameworks acting as the mediating factors is critical to sustainable growth. Complementing this view, Shafi et al. (2025) represent an integrated approach to demonstrate that economic resilience is a result of joint actions of financial inclusion, trade and institutional effectiveness. In addition, panel econometric findings like Shaheen et al. (2025) demonstrate the significance of considering macroeconomic interdependencies, inequality dynamics and endogeneity in the analysis of growth and resilience outcomes. Lastly, there are a number of studies that analyzed structural changes and economic growth models in order to comprehend long-term resilience. Balakrishnan and Parameswaran (2007) have documented the major structural changes in the Indian economic system, in particular, the increasing role of the service sector. Khan et al. (2019) highlighted that agriculture will remain relevant with forward and backward linkages, factor contribution, and foreign exchange earnings despite decreasing its share in gross state domestic product (GSDP). The cause-and-effect relationships between gross domestic product, agriculture and manufacturing, were investigated using econometric models by Singariya and Sinha (2015), which solely supports the importance of sectoral balance. In a similar fashion, Sahoo and Sethi (2012) found out that although agriculture has a very positive contribution to economic growth, the industrial

sector is a more direct contributor to economic growth. So there for both sectors are complementary in achieving sustainable development.

Although there is an increasingly strong research base investigating the macroeconomic effects of shocks such as the COVID-19 pandemic (Coibion, et al., 2020; Rungcharoenkitkul, 2021; Barrett et al., 2021), most studies remain confined to national-level studies, or even simple descriptive comparisons. This perspective doesn't fully acknowledge the considerable differences in financial resources, organizational frameworks and progress patterns among various regions, especially in federal systems like India. Furthermore, there's not much solid proof that directly links state-level capital spending with economic resilience using reliable economic analysis. In the current research, there is a dearth of studies considering fiscal policy variables in a quasi-experimental study to appropriately assess the resilience outcomes. This study intends to investigate the effects of the change in pre-pandemic capital expenditure on the economic resilience of Indian states during the COVID-19 pandemic.

According to the evidence produced by global organizations, such as the International Monetary Fund (2021) and World Bank (2022) and OECD (2021), it is clear that the local fiscal capabilities, infrastructure investment and quality of governance play a significant role in determining the recovery process across the regions. The recent policy reports and empirical analysis (RBI, 2023; NITI Aayog, 2022) indicate that fiscal responses and post-COVID recovery vary significantly across the states in India, hence highlighting the significance of state-level capital expenditure in reducing economic shocks and supporting resilience. Together, these studies imply that capital investment is not only necessary to the long-term growth but also to the ability of regions to endure and recover systemic disruptions. In order to have a more definitive theoretical framework, this paper describes how capital expenditure and economic resilience are related through a detailed causal pathway. The use of public capital is used to enhance productive capacity and efficiency within sectors by creating physical and social infrastructure, i.e., transportation networks, healthcare systems and educational institutions. The improved infrastructure reduces the cost of transactions, market integrations are easier and technology is adopted, resulting in overall increased productivity. Increased productivity, in its turn, makes the economy more resilient to shocks and its recovery and restructuring, which ultimately leads to increased economic resilience.

Table 1: Thematic Synthesis of Literature on Growth, Fiscal Policy and Economic Resilience

Theme	Key Studies	Key Insights	Gap Identified
Growth Theory	Solow (1956), Romer (1990), Barro & Sala-i-Martin (2004)	Capital accumulation and technological progress drive growth	Limited focus on resilience
Fiscal Policy & Investment	Wang et al. (2022), Guru & Yadav (2019)	Public investment enhances productivity and growth	Limited causal evidence at subnational level
Health & Governance	Bhargava et al. (2001), Liu et al. (2018)	Institutional quality and health improve economic performance	Weak linkage to resilience outcomes
Economic Resilience	Briguglio et al. (2014), Duval et al. (2020)	Diversification and fiscal buffers enhance resilience	Mostly cross-country focus

Theme	Key Studies	Key Insights	Gap Identified
COVID-19 & Recovery	Abidi et al. (2023), Mohamed (2023)	Digitalization and fiscal responses support recovery	Limited Indian state-level econometric evidence

1.1 Hypothesis Development

Based on the current theories and studies in the real world, this study proposes a hypothesis that relates fiscal policy to the ability of an economy to bounce back. Economic growth theories indicate that government investments in such aspects as infrastructure can enhance productivity and research on resilience suggests that financial safety nets and good infrastructure can be used to mitigate the effects of unforeseen events. Based on this, the study suggests the following: H1: States with greater per capita GSDP growth rates, in the period following the initial shock, were more economically resilient, with higher levels of per capita capital expenditure growth rates in the post-shock period. This concept implies that capital expenditure enhances the capacity of a region to not only absorb but also adapt to challenges and therefore be in a better position to handle and recover major disruptions in the market such as the COVID-19 pandemic. The second section of this paper will detail the sources of information and how this hypothesis can be tested.

2. Data and Methodology

2.1 Data sources

This study uses information from 29 Indian states over a 20-year period (resulting in 580 data points) from 2003-04 to 2022-23. The sources are: Reserve Bank of India (RBI) Reports, which offers values on gross state domestic product, capital expenditure, credit availability and contributions by various sectors; the EPW Research Foundation Data, which provides a detailed data on sectors and overall economy; and the Global Data Lab, which offers a socioeconomic data relating to education levels, health indices and the Theil index (a measure of income inequality).Table 2 presents a summary of the key variables used in the analysis.

Table 2 Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.
Log Per Capita GSDP	11.278	.602
Log Total Government Expenditure	9.746	.852
Log Per Capita Capital Development Expenditure	7.728	.977
Log GSDP share of agriculture sector	9.445	.617
Log GSDP share of Manufacturing	9.058	1.296
Log GSDP share of Construction	8.736	.537
Log Gross Fiscal Deficit	7.751	.975
Urbanization	34.219	18.497
Log Debt	10.096	.794
Log Credit by Commercial Banks	10.026	1.213
Educational index	.524	.08
Health index	.765	.048
Theil index	.103	.081

2.2 Methodology

This study's empirical approach aims to test our hypothesis by seeing if states that invested more in capital projects before the pandemic fared better economically after the COVID-19 shock. We compare states which received this "treatment" to states which did not, both prior to and following the shock. This assists us in isolating the causal impact of capital expenditure on economic resilience, as well as taking into account unobservable differences in states and general economic patterns over time. Our starting point is a fixed effects (FE) regression model to understand the relationship between per capita GSDP and key economic indicators. This model lets us control for consistent, but unobserved, differences between states. In the present case, a shock will be viewed as an unexpected, sudden event with major consequences significantly interrupting economic activity, employment, public finances or production systems beyond the normal ups and downs. Normal economic variations are the annual-to-annual variation that we encounter in business cycles, seasonal adjustments, moderate changes in demand or even normal revenue changes. Conversely, emergencies such as the COVID-19 pandemic cause widespread and simultaneous disruptions across states, necessitating unusual policy responses. This paper thus regards the COVID 19 pandemic which began in 2020 as the key external shock in determining the extent to which states were well placed to overcome economic hardship.

While there might be concerns that states with stronger economies were able to invest more in capital projects, the Difference-in-Differences design helps reduce this concern by classifying treatment status based on pre-2020 per capita capital expenditure. We didn't use dynamic GMM estimators because our main goal is to identify the causal impact of the shock, rather than model how the effects persist over time.

After establishing these baseline relationships, we use a difference-in-differences (DiD) approach to estimate the causal impact of the COVID-19 shock on per capita GSDP. The DiD method is a widely used quasi-experimental method that compares variations in outcomes between a treatment group and a control group before and after an intervention. The paper considers, states with higher pre-2020, per capita capital expenditure as the treatment group. States with pre-2020, lower capital expenditure serve as the control group. The post-treatment or shock period begins in 2020, marking the beginning of the pandemic's economic effects. The model specification for fixed effects regression and DiD is as follows:

$$\log Y_{it} = \beta_0 + \beta_1 \log X_{1,it} + \beta_2 \log X_{2,it} + \beta_3 \log X_{3,it} + \beta_4 \log X_{4,it} + \beta_5 \log X_{5,it} + \beta_6 X_{6,it} + \beta_7 \log X_{7,it} + \beta_8 \log X_{8,it} + \beta_9 X_{9,it} + \beta_{10} X_{10,it} + \beta_{11} X_{11,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Explanation of model terms

$\log Y_{it}$= Per capita GSDP in log form (Dependent variable), $X_{1,it}$ = Total government expenditure in log form, $X_{2,it}$ = GSDP share of agriculture sector in log form, $X_{3,it}$ = GSDP share of manufacturing in log form, $X_{4,it}$ = GSDP share of construction in log form, $X_{5,it}$ = Gross Fiscal Deficit in log form, $X_{6,it}$ = Urbanization, $X_{7,it}$ = Debt in log form, $X_{8,it}$ = Credit by commercial banks in log form, $X_{9,it}$ = Educational index, $X_{10,it}$ = Health index, $X_{11,it}$ = Theil index, i = i represents the state, t = t represents time (year), β_0 = Intercept term.β_k (k= 1, 2……,11) = Coefficients measuring the effect of explanatory variables on Y_{it}

α_i= α_i represents state fixed effects, $\gamma_{t=}$ $\gamma_t$represents time fixed effects, ε_{it}= ε_{it} is the error term

Difference-in-Differences model

$$\log Y_{it} = \beta_0 + \beta_{12}\, did_{12,it} + \beta_1 \log X_{1,it} + \beta_2 \log X_{2,it} + \beta_3 \log X_{3,it} + \beta_4 \log X_{4,it} + \beta_5 \log X_{5,it} + \beta_6 X_{6,it} + \beta_7 \log X_{7,it} + \beta_8 \log X_{8,it} + \beta_9 X_{9,it} + \beta_{10} X_{10,it} + \beta_{11} X_{11,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Explanation of extra model terms

did_{it} = $Treatment_i \times Post_t$= Interaction term catching the causal effect of COVID-19 on the treated states. $Treatment_i$ = 1 if the state is in the treatment group (pre-2020, high per capita capital expenditure), 0 otherwise. $Post_t$ = 1 if the year is 2020 or later, 0 otherwise

For this analysis, the logarithms of certain variables, such as the share of agriculture, manufacturing and construction in GSDP, along with Credit by Commercial Banks and Total Government Expenditure, have been used in the regression to achieve linearity in relationships. This change allows us to think of coefficients as elasticities and takes the skewness to zero and allows us to handle wide data ranges. Log taking also assists in reducing the effects of outliers, enhances the fit of the model and solves the heteroskedasticity problem, making the estimation more robust. Producing the treated variable to be used in the difference-in-differences analysis. To carry out a Difference-in-Differences (DiD) analysis, states are divided into treated and control groups based on their average per capita capital expenditure before 2020. This categorization helps in examining how COVID-19 has differentially affected economic resilience. To make this classification easy, the median per capita capital expenditure has been computed. To compute average per capita capital expenditure, data between 2003 and 2019 are used to compute average per capita capital expenditure per state.

The definition of the treated variable: States with an average expenditure above the median are assigned as treated (1), while others are controls (0) (Appendix Table 1A). This criterion is suitable as it objectively determines the states with high expenditure that probably indicates a better fiscal stance or a more development-oriented policies. The median makes the difference between the groups significant, thus increasing our chances of identifying differentiating effects in the analysis. In addition, it does not have arbitrary cut-offs and uses a standard, replicable classification method. In the DiD framework, such a stark division of groups enhances the strength of causal inference and enables a more policy-relevant interpretation, particularly when assessing the responses to external shocks such as the COVID-19 pandemic. Establishing the post-treatment or shock measure: To establish the post-treatment or shock measure, a post variable is created that differentiates between the pre-COVID period (0) and the post-2020 period (1). Creation of the interaction term of DiD: A DiD variable is constructed by multiplying the treated variable and the post variable. This captures the differential effect of COVID-19 on high-expenditure states. This approach will provide a sound DiD analysis by comparing the economic resilience of states with varying capital investment levels prior to and following the onset of COVID-19.

Placebo test: In order to guarantee the conclusiveness of the results, a placebo test was conducted by creating a fictitious post-treatment or shock period in 2014 (instead of 2020). The fact that the estimated placebo effect is insignificant would prove that the main results are not subject to any pre-existing trends. The year 2014 was selected as the placebo post-treatment year for this robustness check for two key reasons. First, 2014 is sufficiently close to the actual intervention year (2020) to provide a meaningful test of pre-treatment trends, while still being safely before any real policy changes or external shocks (like the COVID-19 pandemic) that

could have affected the outcomes. This closeness ensures that the economic and institutional environments were generally similar, making it a valid point of comparison. Second, selecting a year like 2014, which falls midway through the pre-treatment period, helps confirm that the parallel trends assumption is holding true. Finding a significant treatment effect during this placebo period would suggest that differences between the groups existed even before the actual treatment, thereby casting doubt on the validity of the DiD design. Therefore, the absence of a significant placebo effect in 2014 increases our confidence that the estimated treatment effects from 2020 onward are genuinely due to the intervention and not to pre-existing differences or trends.

3. Results and Empirical Analysis

The results of the regression of two groups of states, the ones that spend more on average per capita capital expenditure (treated group, model 1) and the ones that spend less (control group, model 2) are presented in Table 3. As we divide the sample on the basis of per capita capital expenditure, we observe that there are certain large differences in the sources of growth. The effect of agriculture and manufacturing shares is positive and significant in both groups, but the magnitude of the effect varies. This informs us that economic structure has a bearing on the growth independent of the amount of fiscal capacity that a state possesses, but the effect is not exactly the same. Construction activity appears to be affecting, much more strongly, states that spend more. What this implies is that investments will still be more rewarding when there is already a good fiscal base and infrastructure in place. On the other hand, total government spending is only notable in states with lower spending implying that as the level of spending increases, the increment in government spending benefit begins to decline.

Table 3 Determinants of Per Capita GSDP: Regression Results for High and Low Capital Expenditure States

Variables Dependent variable: per capita GSDP	Model 1	Model 2
Total Government Expenditure	0.0329	0.122***
	(0.0473)	(0.0336)
GSDP share of agriculture sector	0.265***	0.226***
	(0.0243)	(0.0279)
GSDP share of Manufacturing	0.160***	0.201***
	(0.0104)	(0.0187)
GSDP share of Construction	0.239***	0.0372**
	(0.0240)	(0.0185)
Gross Fiscal Deficit	0.00543	-0.00100
	(0.00750)	(0.00539)
Urbanization	0.00236**	0.00143**
	(0.00108)	(0.000690)
Debt	0.0433	-0.0135
	(0.0294)	(0.00931)
Credit by Commercial Banks	0.0243	0.000731
	(0.0236)	(0.0225)
Educational index	-0.0601	0.568***
	(0.176)	(0.160)
Health index	-0.804***	0.488
	(0.277)	(0.322)

Theil index	1.344***	0.898***
	(0.278)	(0.136)
Constant	4.399***	4.770***
	(0.543)	(0.421)
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	260	278
R-squared	0.981	0.988
Number of States	14	15

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using data from Reserve Bank of India (RBI) Reports, EPW Research Foundation Data and Global Data Lab.

Indicators of human capital reveal that there are some very drastic differences between different groups. The education index turns out to be positive and highly significant only in the states with lower expenditure implying that the benefits of improvements in education are more evident where the starting levels are lower. Interestingly, the health index has negative and significant coefficient in the states with high spending, which is quite unexpected finding. Probably this is not an actual adverse impact. More developed states are likely to allocate more health resources towards dealing with the demographic issue such as ageing population or increased number of diseases. These spending may not directly lead to increased output and composite health indices tend to reflect output as opposed to inputs that increase productivity. Also, the economic gains of health investments usually require time before it is realized. These factors combined form a negative or weak current relationship more structural than causal.

The positive and significant effects of urbanization in both groups are a measure of the productivity gains that are achieved through the concentration of economic activity in urban centres. The Theil index is positive and significant in both groups but with a stronger effect in those states with high expenditure. This implies that the more industrialized and heterogeneous economies are expected to generate higher incomes as well as greater inequality. This is once again a structural pattern and not a causal mechanism. On the whole, high expenditure states have more growth which is led by sectoral and structural factors. In contrast, the low expenditure states are more sensitive to the expenditure and enhancement of the human capital and the initial fiscal conditions play a central role in the analysis of the subnational economy.

The findings of a difference-in-differences (DiD) regression with fixed effects were presented in table 4 and analyzed the effect of capital expenditure on economic resilience during the COVID-19 pandemic. The dependent variable is the logarithm of per capita GSDP, while the independent variables include sectoral GSDP shares, credit availability, government spending, debt, urbanization, gross fiscal deficit and socioeconomic indices like education, health and inequality. The DiD coefficient is positive and significant at the 5% level (0.044). This implies that states that had increased per capita capital expenditure prior to 2020 would have on average about 4.4% higher per capita GSDP in the post-COVID period than states that had lower expenditure. It contributes to the hypothesis that, higher levels of public investment before the pandemic make the economy more resilient to external shocks.

Table 4 Fixed Effects Difference-in-Differences Regression

Variables Dependent variable: per capita GSDP	Model 1
DiD	0.0440**
	(0.0212)
Total Government Expenditure	0.0690
	(0.0558)
GSDP share of agriculture sector	0.239***
	(0.0561)
GSDP share of Manufacturing	0.191***
	(0.0172)
GSDP share of Construction	0.148***
	(0.0485)
Gross Fiscal Deficit	0.00305
	(0.00504)
Urbanization	0.00182
	(0.00113)
Debt	-0.0149
	(0.0209)
Credit by Commercial Banks	0.0376
	(0.0371)
Educational index	0.147
	(0.270)
Health index	-0.391
	(0.573)
Theil index	0.731**
	(0.353)
Constant	4.889***
	(0.990)
State Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	538
Number of States	29
R-squared	0.978

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using data from Reserve Bank of India (RBI) Reports, EPW Research Foundation Data and Global Data Lab.

The composition of different sectors continues to be a key factor influencing economic outcomes. The positive and significant shares of agriculture, manufacturing and construction strengthen the trends that we saw in our original fixed-effects results. This constantly indicates that productive structure is one of the key factors in various models. The overall government spending, fiscal deficit, debt and credit do not appear to have a statistically-significant effect in this particular analysis. Since the difference-in-differences design and the fixed effects design takes into account the difference in the effects between states, their immediate and short-term contributions are more difficult to identify. Among the level variables that we studied, urbanization demonstrates a positive but insignificant impact and the education index is also weakly identified. The health index has a negative coefficient, yet, it is also unimportant. This

does not necessarily imply that there is a causal negative impact as we determined in Table 3. More developed states, most of which belong to the treated group, are more likely to spend more on health, because of factors such as demographics and prevalence of various diseases. But this expenditure does not directly lead to an increase in output in the short run. Healthcare benefits are also likely to manifest themselves in the long run. Result-based indexes may not be able to adequately measure productivity-enhancing inputs, which results in poor or even negative correlations in the current period.

The Theil index, a measure of inequality, is positive and significant at the 5% level, indicating structural differences between states. More economically developed and industrialized states have higher average incomes, yet have larger income inequalities. This is probably a factor of urbanization, diversification in the sector and benefits of scale and not a direct causal relationship between inequality and growth. The other factor is small states outliers such as Goa and Sikkim. Very high per capita income levels and distinct fiscal structures due to small populations, dependency on tourism or hydropower or other special economic features are common in such states. Consequently, their per capita measures might appear disproportionately big when contrasted with bigger states. Nonetheless, the fixed-effects model aids in addressing these issues by conditioning the effects of state-specific variations that do not vary. However, the fixed-effects model can help in addressing these issues by controlling the effects of state-specific variations that do not change over time. This implies that our analysis is concerned with how the states have changed over time as opposed to just comparing states to each other. So, these outliers may have an impact on descriptive averages, but they are less likely to have an impact on the core difference-in-differences estimate. On the whole, our results provide significant evidence on the role of capital expenditure in the enhancement of economic resilience. States that put more emphasis on infrastructure and investments in capital were in a better position to overcome the economic difficulties of the pandemic. Simultaneously, the dynamics we have seen in areas of economic activity and social parameters imply that balanced growth is required. This implies the integration of investment with encouragement of major sectors and policies encouraging equity towards sustainable and inclusive development.

Placebo Test

To further see to it that our causal interpretation is true, we did a placebo test (Table 5). In this test, we assumed that the post-treatment or shock period began in 2014, rather than in 2020 (the actual post-pandemic period). This placebo difference-in-differences coefficient is positive, but not statistically significant (0.029). This is in line with the assumption of parallel trends, i.e., there were no systematic differences in the trends in the treated and control states before the actual COVID-19 shock. The absence of a placebo effect adds more weight to our conviction that the large difference-in-differences estimate post 2020 is indeed a reflection of the divergence related to the pandemic and not a pre-existing difference between the states.

Table 5 Placebo Test Results-Fixed Effects Difference-in-Differences Regression

Variables Dependent variable: per capita GSDP	Model 1
Placebo-DiD	0.0294
	(0.0279)
Total Government Expenditure	0.0810
	(0.0533)
GSDP share of agriculture sector	0.237***
	(0.0548)
GSDP share of Manufacturing	0.190***
	(0.0170)
GSDP share of Construction	0.143***
	(0.0483)
Gross Fiscal Deficit	0.00304
	(0.00496)
Urbanization	0.00183
	(0.00114)
Debt	-0.0161
	(0.0207)
Credit by Commercial Banks	0.0436
	(0.0367)
Educational index	0.160
	(0.265)
Health index	-0.473
	(0.561)
Theil index	0.699*
	(0.363)
Constant	4.867***
	(1.005)
Observations	538
Number of States	29
R-squared	0.978

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using data from Reserve Bank of India (RBI) Reports, EPW Research Foundation Data and Global Data Lab.

The behaviour of the control variables is a close replica of the main specifications. The sectoral shares of agriculture, manufacturing and construction remain to be positive and highly significant supporting the notion that the structural composition is one of the key factors to drive growth. Government spending, fiscal deficit, debt and credit are all insignificant which is consistent with their relatively minor roles in the difference-in-differences (DiD) model of the baseline. As we can see in the level variables, urbanization and the education index are positive and again not significant, and the health index is negative and not significant again. The structural interpretation as given in Tables 3 and 4 is equally applicable here. The states that have higher fiscal capacity have increased expenditures on health services in response to demographic pressures. Yet, the economic benefits of this spending are not instant and require time to manifest and are not visible in the present time. The Theil index is still positive and weakly

significant which may indicate that it is an indicator of structural transformation rather than a cause.

Robustness

To check the robustness of the DiD results, we included a lagged dependent variable to account for stability in economic performance (Table 6). The lagged per capita GSDP is positive and highly significant (0.543), suggesting that about half of current income depends on last year's income. This shows strong stability in state-level growth and indicates that ignoring it would overstate the effects of current-period variables.

Table 6 Robustness check with lagged dependent variable

Variables Dependent variable: per capita GSDP	Model 1
Lagged Per capita GSDP	0.543***
	(0.0718)
DiD	0.0169*
	(0.00903)
Total Government Expenditure	0.0466
	(0.0283)
GSDP share of agriculture sector	0.136***
	(0.0240)
GSDP share of Manufacturing	0.0947***
	(0.0167)
GSDP share of Construction	0.0677**
	(0.0258)
Gross Fiscal Deficit	0.00169
	(0.00324)
Urbanization	4.40e-05
	(0.000586)
Debt	-0.00680
	(0.00862)
Credit by Commercial Banks	0.0186
	(0.0191)
Educational index	0.0503
	(0.112)
Health index	-0.138
	(0.290)
Theil index	0.329*
	(0.181)
Constant	1.829***
	(0.614)
State Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	511
Number of States	29
R-squared	0.988

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using data from Reserve Bank of India (RBI) Reports, EPW

Research Foundation Data and Global Data Lab.

Once past income effects are taken into account, the DiD coefficient decreases from 0.044 to 0.017, becoming only weakly significant at the 10% level. This decline is to be expected, as the lagged variable soaks up pre-existing growth patterns that the baseline DiD partially reflects. Nevertheless, the coefficient remains positive, suggesting that states with stronger fiscal capacity before the pandemic still exhibit relatively better performance post-COVID, although the effect is more moderate. This hints that a portion of the primary result stems from existing growth momentum rather than an independent fiscal capacity channel.

Sectoral variables maintain their positive and significant status, although with smaller magnitudes than in the baseline. This indicates that, once past income is factored in, the marginal impact of sectoral composition is more subtle but still noteworthy. Government expenditure, fiscal deficit, debt and credit variables remain insignificant, which is consistent across all specifications.

Among level variables, urbanization essentially drops to zero, implying that its influence is already integrated within lagged income dynamics. Education is also insignificant, while the health index remains negative but insignificant. This can be attributed to factors discussed earlier, such as demographic-driven health spending in developed states, where the benefits of such spending take time to translate into productivity gains. Additionally, outcome-based measures may not fully capture the short-term contribution of health investments to output.The Theil index remains positive, but its magnitude decreases significantly to 0.329 and shows only weak significance. This further solidifies the notion that the association between inequality and income is structural. Once income persistence is considered, the Theil index's role as a proxy for development stage diminishes, leaving a modest remaining association.

Overall, the dynamic model lends support to the primary results. The DiD effect persists, although diminished, indicating that the findings are not solely attributable to past growth patterns. This suggests that pre-pandemic fiscal capacity indeed plays a genuine role in shaping economic resilience.

4. Conclusion and Policy Directions

This study enhances our understanding of economic resilience by demonstrating that Indian states with higher per capita capital development expenditure leading up to the COVID-19 pandemic displayed stronger economic performance after the shock. This is reflected in a 4.4 percent increase in per capita GSDP growth. Through a DiD approach, the analysis validates that capital investment, particularly in long-term public infrastructure, serves as a stabilizing force and promotes growth during systemic crises.More importantly, this paper identifies varying patterns in how different states respond to shocks, revealing heterogeneous impacts depending on fiscal capacity and structural composition. States that were treated experienced greater gains from the agriculture and manufacturing sectors. This suggests that they possessed superior structural preparedness and resources to weather the economic shock. Conversely, control states exhibited a stronger reliance on government expenditure and improvements in health, indicating resilience mechanisms rooted in social investment rather than fiscal outlays. This comparative insight highlights a crucial policy implication: a one-size-fits-all strategy for economic resilience does not exist. While fiscal robustness (capital investment) remains vital, social sector

investments, especially in health and inclusive spending, also play a significant role, particularly in states with less fiscal capacity.

Furthermore, the positive correlation between inequality (Theil index) and growth in the post-pandemic period raises concerns regarding the distributional effects of resilience. The benefits of recovery may be disproportionately accruing to specific sectors or regions, which could erode social unity and long-term sustainability if left unaddressed.

Based on these findings, the following policy directions are proposed:Prioritize Capital Expenditure: States should increase investments in infrastructure, education and healthcare to foster long-term economic resilience.Ensure Inclusive Growth: Addressing income inequality and promoting financial inclusion are essential for ensuring that the benefits of growth are widely shared.Strengthen Financial Systems: Expanding access to credit and financial instruments can stabilize the economy and support productive investment.

The analysis relies on aggregate state-level data, which may mask intra-state variations across districts, sectors and population groups. Therefore, the findings represent average state-level effects rather than uniform outcomes within states. Although pre-treatment expenditure mitigates concerns about simultaneity, some endogeneity may persist due to omitted institutional or governance factors. While this study offers valuable insights, future research could explore the long-term impacts of capital expenditure beyond the immediate post-COVID-19 period. Investigate the role of institutional quality and governance in the effectiveness of fiscal policy and identify sector-specific interventions that promote both recovery and equity.In conclusion, the study highlights the critical role of capital expenditure in strengthening economic resilience, providing compelling empirical support for designing fiscal policies that are proactive, inclusive and responsive to future economic shocks.

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Appendix

Table 1A: Indian States by Pre-Average Per Capita Capital Expenditure: Treatment vs. Control Groups

States	Pre-Average per capita capital expenditure	Treatment variable
Andhra Pradesh	2361.818	1
Arunachal Pradesh	10597.25	1
Assam	1158.365	0
Bihar	993.4221	0

Chhattisgarh	1768.145	0
Goa	6094.421	1
Gujarat	2424.082	1
Haryana	2130.419	1
Himachal Pradesh	3099.186	1
Jharkhand	1504.066	0
Karnataka	2570.247	1
Kerala	1186.973	0
Madhya Pradesh	1699.024	0
Maharashtra	1590.559	0
Manipur	3756.093	1
Meghalaya	2302.771	0
Mizoram	6495.7	1
Nagaland	4070.069	1
Odisha	1928.198	0
Punjab	1023.943	0
Rajasthan	1445.229	0
Sikkim	9770.934	1
Tamil Nadu	1805.378	0
Tripura	3542.526	1
Uttar Pradesh	1445.663	0
Uttarakhand	2879.436	1
West Bengal	740.0138	0
Delhi	1878.0	0
Jammu and Kashmir	4155.786	1

Source: Authors' calculations using data from Reserve Bank of India (RBI) Reports, EPW Research Foundation Data and Global Data Lab.

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AN ARTIFICIAL NEURAL NETWORK-ASSISTED ZERO-RIPPLE HIGH-GAIN POWER INTERFACE FOR PHOTOVOLTAIC DC MICROGRIDS

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ABSTRACT

The rapid integration of renewable energy sources, particularly photovoltaic (PV) systems, into the modern electrical grid demands highly efficient power electronic interfaces. PV modules inherently produce low-level DC voltages, necessitating the use of high-gain DC-DC boost converters to step up the voltage for grid-tied inverters or high-voltage DC loads. However, conventional boost converters operating at extreme duty cycles suffer from severe efficiency degradation, high voltage stress on semiconductor switches, and significant input current ripples. High input current ripple is particularly detrimental to PV systems, as it accelerates the aging of the solar panels and reduces the overall energy harvesting efficiency. This paper presents the comprehensive analysis, closed-loop design, and intelligent control of a transformer-less high-gain boost converter featuring input current ripple cancelation. The base topology uniquely combines two interleaved input inductors with a switched-capacitor (SC) voltage multiplier stage to achieve a high voltage gain without the need for coupled inductors, bulky transformers, or extreme duty ratios. By mathematically sizing the interleaved inductors such that L2=3L1, the converter theoretically achieves a zero input current ripple at a nominal duty cycle of D=0.75. To optimize this topology for dynamic real-world PV applications, this research introduces an advanced Artificial Neural Network (ANN) for Maximum Power Point Tracking (MPPT). The ANN was trained using a highly granular dataset of 100,000 continuous data points encompassing varying irradiance (100-1000 W/m²) and temperature (15°C-65°C) profiles. The trained neural network, consisting of a 15-neuron hidden layer, achieved an exceptional regression accuracy of R=0.9999. A discrete Proportional-Integral (PI) controller was developed to regulate the duty cycle, stabilizing the output voltage at 80V from a 15V input source. Furthermore, by increasing the switching frequency to 40 kHz, discrete micro-ripples were entirely eliminated, resulting in a perfectly flat input current waveform. The proposed closed-loop intelligent system was thoroughly modeled, simulated, and validated using the

MATLAB/Simulink environment, demonstrating superior transient response, high voltage gain, and ideal ripple-free operation.

KEYWORDS: *Artificial Neural Network, Boost Converter, Dc Microgrid, Maximum Power Point Tracking (Mppt), Photovoltaic Systems, Switched-Capacitor, Zero-Ripple.*

I. INTRODUCTION

A. Background and Motivation

The global transition toward sustainable and clean energy has accelerated the deployment of distributed generation systems, with solar photovoltaic (PV) technology leading the market. Despite the widespread adoption of PV systems, extracting maximum available power and efficiently transferring it to the load or grid remains a complex engineering challenge. A fundamental characteristic of individual PV modules is their relatively low output voltage, which typically ranges from 15V to 40V depending on the environmental conditions and the specific semiconductor configuration. To interface these low-voltage sources with standard DC buses (e.g., 380V or 400V) or grid-connected inverters, a highly efficient power processing circuit capable of achieving a massive voltage step-up is strictly required.

Conventional boost converters are theoretically capable of infinite voltage gain as the duty cycle approaches unity. However, in practical hardware implementations, the voltage gain is severely limited by the parasitic equivalent series resistance (ESR) of the inductors, the on-state resistance of the power switches, and the forward voltage drops of the diodes. Operating a standard boost converter at extreme duty cycle values (e.g., $D > 0.9$) leads to reverse-recovery problems in diodes, massive conduction losses, and catastrophic efficiency drops, making extreme duty cycle values highly undesirable.

B. The Challenge of Input Current Ripple in PV Systems

Another primary challenge in renewable-energy power processing circuits is the expected low input current ripple. PV panels are highly sensitive to the current drawn from them. High-frequency AC current ripples superimposed on the DC current cause the operating point of the PV panel to oscillate around the Maximum Power Point (MPP), leading to a continuous loss of harvestable power. Furthermore, severe current ripples cause internal thermal cycling within the delicate semiconductor junctions of the solar cells, significantly accelerating their degradation and shortening the operational lifespan of the solar array.

The standard industry solution to mitigate input current ripple is the utilization of large input inductors. While large inductors lead to a small current ripple, they are heavily disadvantaged by their large size, immense weight, and high cost. In addition to the physical drawbacks, a large inductor inherently slows down the transient response of the power converter, making it sluggish and unable to react rapidly to fast-changing atmospheric conditions such as passing clouds.

C. Review of MPPT Techniques

To maximize energy harvesting, the PV system must continuously operate at the peak of the P-V curve. MPPT algorithms are broadly classified into conventional methods and advanced artificial intelligence (AI) based methods:

Perturb and Observe (P&O): This method operates by periodically perturbing the operating voltage and observing the change in output power. While simple, P&O suffers from continuous steady-state oscillations around the MPP, leading to power loss, and it frequently fails to track the true MPP during rapidly changing weather conditions.

Incremental Conductance (INC): INC improves upon P&O by utilizing the derivative of power with respect to voltage (dP/dV = 0 at the MPP). While it reduces steady-state oscillations, INC requires complex division calculations and remains vulnerable to sudden irradiance drops.

Fuzzy Logic Controllers (FLC): FLCs handle PV nonlinearities using heuristic rule bases, but their performance heavily depends on the designer's expertise in defining membership functions and rule tables. They also suffer from high computational complexity.

Artificial Neural Networks (ANN): ANNs have emerged as powerful data-driven MPPT controllers. By learning the exact nonlinear relationship between the environment and the optimal voltage (Vmpp), an ANN instantaneously calculates the MPP without searching, resulting in zero steady-state oscillations and ultra-fast tracking.

D. Problem Statement and Proposed Solution

The integration of low-voltage PV arrays requires a power converter that can achieve a high step-up ratio without extreme duty cycles, while simultaneously maintaining a strictly zero-ripple input current to preserve PV lifespan. Standard linear controllers and traditional MPPT algorithms struggle to track the optimal voltage rapidly without inducing steady-state oscillations.

This paper addresses these combined gaps by proposing the integration of an Artificial Neural Network MPPT controller with a Transformer-less High-Gain Boost Converter featuring Input Current Ripple Cancelation. The proposed circuit utilizes an asymmetric interleaved input stage to achieve mathematically perfect zero-ripple current, combined with an SC voltage multiplier cell to achieve massive voltage gain at a nominal duty cycle.

II. PROPOSED CONVERTER TOPOLOGY AND ANALYSIS

A. Overview of Proposed System Configuration

To overcome the limitations of traditional boost converters, a novel transformer-less high-gain boost converter is utilized. The topology strategically merges an interleaved input inductor stage for current ripple cancellation and a Switched-Capacitor (SC) voltage multiplier stage to step up the output voltage. By avoiding magnetic coupling and transformers, the circuit eliminates leakage inductance, thereby reducing voltage spikes and improving overall efficiency.

The schematic consists of two active power switches (S_1 and S_2), three diodes (D_1, D_2, and D_3), three capacitors (C_1, C_2, and C_3), and two main energy-storage inductors (L1 and L2). A very small resonant inductor (L_3) is placed in series with diode D_3 to limit peak current spikes. The primary duty cycle D is defined as the percentage of the switching period (Ts) during which switch S_2 is turned ON, while S_1 is driven by the complementary signal for (1-D) Ts.

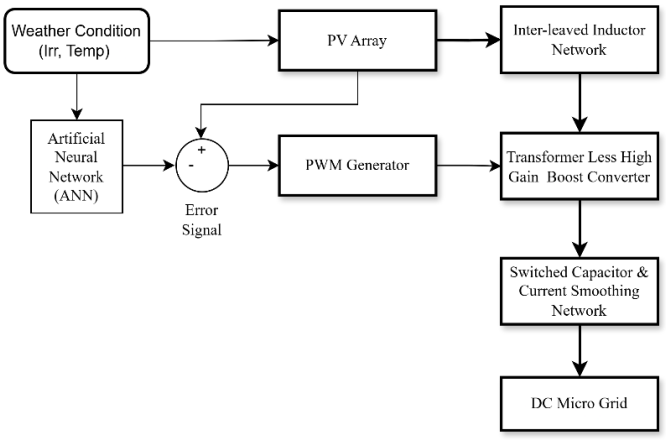

Figure 1. Block Diagram of Proposed System

B. Modes of Operation

Mode 1: Switch S_2 is ON, Switch S_1 is OFF

(0 < t < DTs)

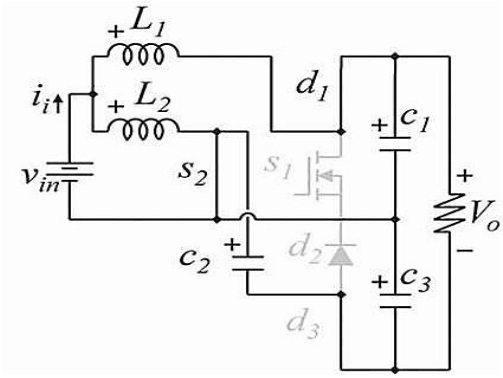

Figure 2. Equivalent circuits for the two complementary switching states during Mode 1

During this interval, L_1 discharges its stored energy into capacitor C_1 through the input source. Simultaneously, L_2 charges directly from the input DC source (Vin) through the closed switch S_2. Because S_2 is closed, capacitor C_2 is placed in parallel with capacitor C_3 via diode D_3 and inductor L_3, forcing C_3 to charge to the same voltage level as C_2.

Mode 2: Switch S_1 is ON, Switch S_2 is OFF

(DTs < t < Ts)

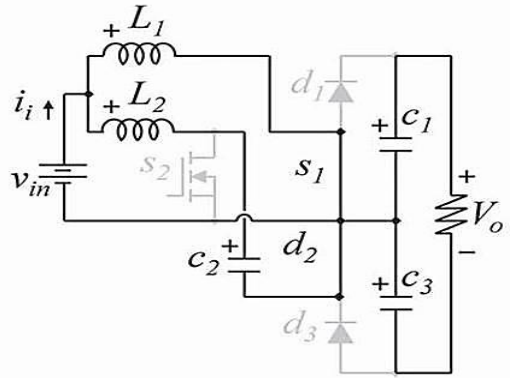

Figure 3. Equivalent circuits for the two complementary switching states during Mode 2

Inductor L_1 charges directly from Vin, while L_2 discharges its energy into capacitor C_2 via diode D_2. The parallel connection between C_2 and C_3 is broken, and diode D_3 becomes reverse-biased. Capacitor C_1 and C_3 are connected in series with the load, supplying the total output voltage.

C. Steady-State Voltage Gain Analysis

Applying the principle of inductor volt-second balance to L_1 yields:

$$D(Vin - VC1) + (1-D)(Vin) = 0$$

Solving for VC_1:

$$VC_1 = Vin / D$$

Applying volt-second balance to inductor L_2 yields:

$$D(Vin) + (1-D)(Vin - VC2) = 0$$

Solving for VC_2:

$$VC_2 = Vin / (1-D)$$

Due to the switched-capacitor action during Mode 1:

$$VC_3 = VC_2 = Vin / (1-D)$$

The total output voltage (V0) is the sum of the voltages across C_1 and C_3:

$$V_0 = VC_1 + VC_3$$

The ideal voltage gain of the converter is given by:

$$V_0 / Vin = 1 / [D(1-D)]$$

For the specific nominal operating point designed in this work (D = 0.75), the theoretical voltage gain is 5.33, naturally boosting a 15V PV input to 80V.

D. Input Current Ripple Cancellation Analysis

The total input current (iin) is the direct sum of the currents flowing through L_1 and L_2. The individual peak-to-peak current ripples are dictated by their charge cycles:

$$\Delta iL_1 = (Vin / L_1) * (1-D)Fs$$

$$\Delta iL_2 = (Vin / L_2) * D\,Fs$$

The total input current ripple (Δiin) is the difference between the two individual ripples:

$$\Delta iin = (Vin / Fs) * [D/L2 - (1-D)/L1]$$

Equating this to zero yields the ripple cancellation condition:

$$L_2 = L_1 * [D / (1-D)]$$

For D=0.75, the required inductor ratio is $L_2 = 3L_1$ (e.g., L_1=280µH and L_2=840µH).

III. ARTIFICIAL NEURAL NETWORK BASED MPPT DESIGN

A. Need for ANN-MPPT

Artificial intelligence-based MPPT methods were developed to overcome issues of conventional trackers, specifically avoiding steady-state oscillations and ensuring rapid response. The ANN

acts as an intelligent estimator that receives environmental conditions as inputs and produces the optimum reference voltage (Vmpp) corresponding to the maximum power point.

B. Development of Training Data

A large synthetic dataset containing exactly 100,000 samples was generated to represent the relationship between irradiance (100 to 1000 W/m²), temperature (15°C to 65°C), and the required maximum power point voltage. The dataset generation followed the empirical model:

$$Vmpp = 15 - 0.05(T - 25) + 0.8 \ln(G / 1000)$$

Where G is irradiance and T is temperature. This analytical expression emulates a practical low-voltage PV source around a 15V nominal operating region.

C. Network Architecture and Training

A feed-forward neural network was selected consisting of 2 input neurons, a hidden layer of 15 neurons, and 1 output neuron. The complete dataset was divided into 70% for training, 15% for validation, and 15% for testing. The network was trained using the Levenberg-Marquardt optimization method, rapidly reaching convergence without overfitting.

IV. CLOSED-LOOP CONTROL STRATEGY AND IMPLEMENTATION

A. Control Structure

The proposed control architecture is arranged in cascade form. The outer layer is the ANN-based MPPT estimator, while the inner fast loop is a voltage-regulation loop using a PI controller. The control error is processed as:

$$e(t) = Vmpp^* - Vmeas$$

The PI control law in continuous form is:

$$u(t) = Kp\, e(t) + Ki \int e(t)dt$$

In the Simulink implementation, a discrete PI controller was employed for numerical stability and digital implementation realism.

B. Duty-Cycle Initialization and PWM Generation

The controller was initialized around the nominal duty ratio (D=0.75) to avoid large initial startup ripples and transient disturbances. A saturation block restricts operation to a stable region near the designed ripple-cancellation point. The PWM generator compares the limited duty command with a carrier waveform, generating complementary switching logic for S1 and S2.

V. SIMULATION RESULTS AND DISCUSSION

A. Simulation Parameters

The entire system was constructed and tested within MATLAB/Simulink using a fixed-step discrete solver with a sample time of 1e-5 s. Key parameters include: Vin=15V, Vout=80V, D=0.75, fs=40 kHz, L_1=280µH, L_2=840µH, and Cout=100µH.

B. ANN Training Results

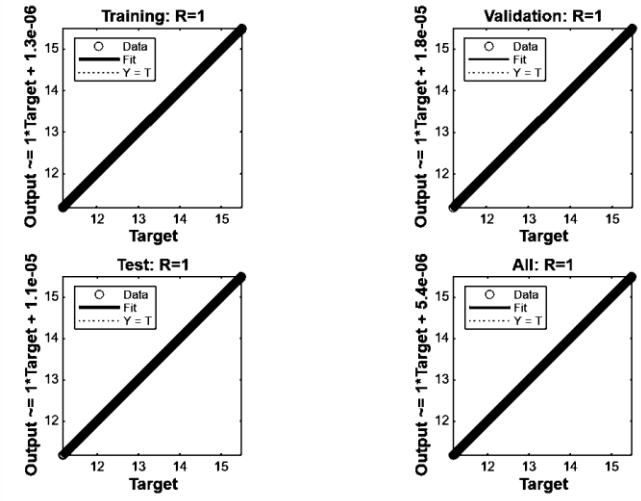

Figure 4. MATLAB Regression analysis

The regression analysis demonstrated exceptional accuracy, with correlation coefficients (R) for training, validation, and testing all converging to R=0.9999. This ensures the ANN perfectly learned the nonlinear characteristics, eliminating steady-state MPPT oscillations.

C. Open-Loop Zero-Ripple Verification

Applying a constant duty cycle of D=0.75 yielded an exact 80V output from a 15V input, validating the theoretical voltage gain of 5.33. The individual currents through L_1 and L_2 exhibited large, distinct triangular ripples. However, sized precisely at $L_2=3L_1$, these individual ripples perfectly canceled each other out at the input node, resulting in a flat, continuous DC line for the total input current (Iin).

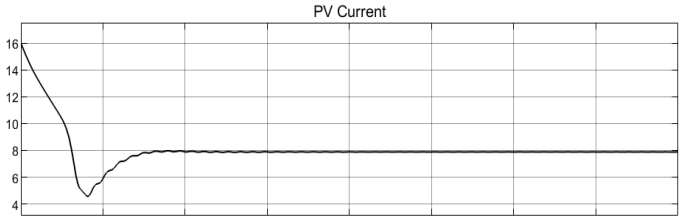

Figure 5. Ripple free input current

The system was tested as a grid-feeding source connected to an 80V DC Microgrid. The microgrid forcibly stabilizes the output voltage, necessitating control of the input PV parameters. The injected power (Pinj) is directly proportional to the current pushed across the line resistance:

*Pinj = Vmg * (Vout - Vmg) / Rline*

During sudden irradiance step-downs (e.g., from 1000 W/m² to 600 W/m²), the ANN instantaneously recalculated the new optimal Vmpp reference. The PI controller smoothly adjusted the duty cycle, successfully decoupling the non-linear PV dynamics from the rigid microgrid.

E. Frequency Optimization

Initial tests at 20 kHz left measurable traces of current ripple. By increasing the switching frequency to 40 kHz, the charging time constant was drastically reduced. Output measurements

recorded an average DC current of 3.1250 A with a fundamental peak of 0.008938 A, resulting in a total ripple percentage of 0.2022%. This ultra-low ripple (<2%) acts as a pure DC extraction, maximizing PV cell health.

VI. CONCLUSION AND FUTURE SCOPE

This paper proposed, mathematically analyzed, and validated an intelligent zero-ripple, high-gain power converter for low-voltage PV microgrid applications. The interleaved inductor configuration successfully eliminated input macro-ripple at a D=0.75 nominal operating point via an exact $L_2=3L_1$ ratio. Simultaneously, the SC multiplier stage achieved a 5.33 voltage gain (15V to 80V) without magnetic isolation or extreme duty cycles.

The integration of a highly trained Artificial Neural Network (trained on 100,000 data points with R=0.9999) enabled instantaneous, oscillation-free tracking of the maximum power point during rapidly changing weather conditions. Future work will focus on implementing a physical laboratory prototype utilizing wide-bandgap SiC or GaN MOSFETs and executing real-time digital control via DSPs or FPGA platforms.

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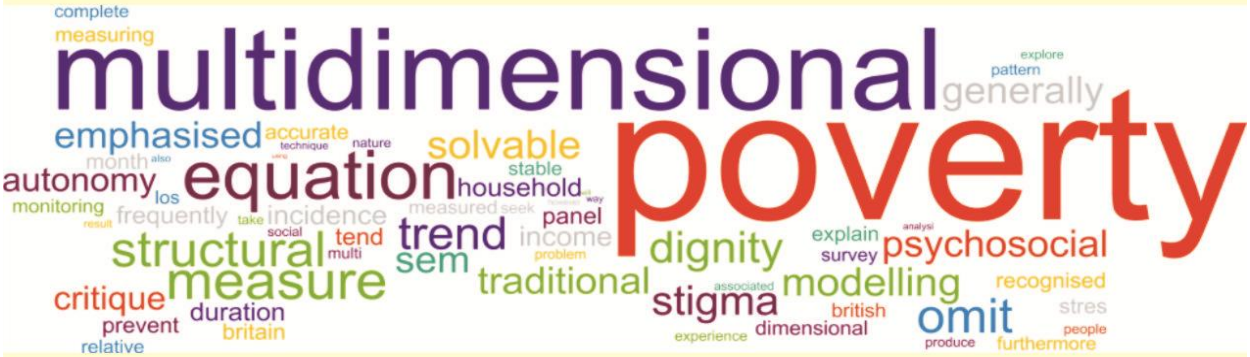

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